INFORMATION TRANSFER, MICROSTRUCTURES AND ARBITRAGE
IN RELATED STOCK AND FUTURES MARKETS

by

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A thesis submitted for the degree of Doctor of Philosophy of the Australian National University

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In compliance with the requirements relating to admission to examination and submission of theses, for the Degree of Doctor of Philosophy of The Australian National University, I hereby certify that, unless otherwise stated, the work that follows is my own and has not been submitted for higher degree to any other Institution or University.

Allan Clement Hodgson
ACKNOWLEDGMENTS

I would like to thank a number of people who provided invaluable assistance and advice during the course of this study. Des Nicholls, as Chairman of my supervisory panel, provided encouragement, constructive feedback and technical advice on the draft chapters. To the other members of my supervisory panel, John Okunev and Ben Hunt, I thank them for their valued input. Mohammad Tahir, my academic colleague at the ANU, provided friendship and support in the form of ideas and feedback on chapters. Roger Willett, Barry Oliver, Pradeep Yadav, Stephen Brown and Mark Tippett also assisted during various stages. Marian Young and Jill Hoffmann provided typing assistance and Christina Jankovic, Kathy MacLaren, Yushan Long and Mark Zhang provided research assistance. I am especially grateful to Mark for programming assistance and his patience in helping me to master the SAS system in the formative stages.

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ABSTRACT

A general result from theoretical and empirical research in financial markets is that information, market microstructures and trading clientele affect prices and trading patterns. Previous research, however, concentrated mainly on larger well traded security markets. This thesis extends this research to the thinly traded and informationally dependent Australian All Ordinaries Index (AOI), the Share Price Index (SPI) futures contract and the arbitrage pricing series between these two markets. Time series and transfer function techniques are applied to intraday and interday data to examine the impacts of information flow and trading structures on trading and price patterns and the spillover effects across markets.

The empirical evidence from this thesis is consistent with a number of complex and dynamic relationships which vary across trading times and market places. Results indicate that in individual AOI and SPI markets, structural trading halts, price setting mechanisms, and the arrival of information at market opening are associated with price overreaction and higher volatility, but this is not the case in the arbitrage price series. At the close of trading there are significant average price deviations in the individual and arbitrage series, but without any excess price volatility. Unexpected intraday trading activity in the futures market preceded price changes in the stock and futures markets; the arrival of information has a greater impact on futures prices and the short term volatility in the futures markets is significantly higher than in the stock market. These influences in the futures market, however, did not lead to any spillover effects which increased the long term volatility of the stock market. However, there is evidence of sustained and predictable mispricing in the SPI index futures arbitrage series with mean reversion in the arbitrage series being a function of different times of the day and possible market psychology. On the other hand, significant mean reversion is associated with increased trading volume and efficient transaction cost bound arguments.

Overall, the research in this thesis indicates that markets are affected by a mixture of information, trading microstructures and subtle market reactions, which are both rational and irrational. The major conclusion is that price and volume reactions are complex and flexible theories are required to explain the intricate workings of the marketplace. These are important considerations to be borne in mind by policy makers, regulators and market traders.
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CHAPTER ONE

AN INTRODUCTORY NOTE

1.1 INTRODUCTION

This thesis is concerned with developing a detailed and comprehensive empirical understanding of the impact of information flows on price returns, volatility, trading volume, and arbitrage pricing across cash and futures markets. The analysis encompasses both exogenous international impacts and the spillover or feedback across the related markets. The securities chosen for analysis are the Australian Stock Exchange's All Ordinaries Index (AOI)\(^1\) and the derivative Share Price Index (SPI)\(^2\) futures contract. The primary data set analysed consists of 15-minute observations of the AOI and the SPI over the period 1 April 1992 to 30 March 1993. A secondary data set consists of closing AOI prices from 2 February 1981 through 30 June 1987.

Whilst the primary focus is on analysing the transfer effects of information, the analysis may be affected by the underlying microstructures of the different markets and the information feedback across cash and futures markets. This implies that there will be secondary considerations and a knowledge of the impact of market microstructures, and arbitrage and feedback relations between cash and futures markets is also required.

---

\(^1\) The AOI is a capital gains index comprised of the market prices of approximately 250 listed shares which represents about 80% of the capitalised value of all Australian shares.

\(^2\) The SPI futures contract is written on the AOI, and was introduced to the Sydney Futures Exchange (SFE) in February 1983.
The motivations for the thesis are the spectacular growth in the different kinds of financial derivative securities traded on the SFE, recent microstructure research, the international linkages across markets, the impact of information on prices, and the growing anomalies literature. A secondary motivation is provided by the fact that comparably little research has been undertaken on the micro evolution of prices in futures markets and this is particularly the case in Australia.

There are a number of contributions which this thesis makes. The first is to provide empirical evidence on the impact of overnight public information on intraday prices and the arbitrage price in the Australian stock and futures markets. The second contribution is to apply transfer function time series models in order to capture these information impacts. This is done by modelling the impact of information as instantaneous, diffusion or lagged diffusion, or oscillating overreaction processes. The third contribution is to compare and contrast the microstructure effects on markets by describing the intraday evolution of prices in stock and futures markets which have different trading microstructures. The fourth contribution is to overcome the nonsynchronous trading problem in Australia, by analysing the arbitrage mispricing series derived from a much finer information set than has previously been used. The fifth contribution is to analyse the impact of derivative futures trading on the long run volatility of the underlying stock market. The sixth contribution is to add empirical evidence to the debate on whether mean reversion in futures mispricing is caused by arbitrageurs or is a 'statistical illusion'. Finally, an overall contribution of the thesis is to extend the empirical research into a small informational dependent stock market with different trading structures, and to compare the results to the research generated in larger, thickly traded markets.

The remainder of this introductory chapter first provides a background to futures trading in Australia followed by a brief summary of the growth and economic justification of stock index futures contracts. This is followed by an overview of the chapters contained in this thesis along with a justification and a background to the research problems examined in each chapter.
1.2 BACKGROUND

Prior to 1980, trading on the SFE mainly consisted of futures contracts written on rural commodities (eg. wool, live cattle, export beef, fat lambs and gold futures). Since January 1983, when the SPI futures contract written on the underlying AOI was first traded, there has been a general expansion in trading in financial derivatives in Australia. The SFE now trades financial futures in 90-day bank bill, 3-year treasury bonds, 10-year treasury bonds, and the All Ordinaries SPI; and option contracts written on these contracts.

An indication of the annual growth of trading volume in financial futures and futures option contracts is given in Table 1.1. In 1980 less than 3% of contracts traded on the SFE were financial derivatives. By 1994, over 99% of annual futures contract trading volume was in financial futures or options. At the same time total trading volume on the SFE increased from 617,802 contracts to 28,795,938. The annual trading volume in the All Ordinaries SPI futures contract has increased from 180,014 contracts in 1983 to 2,719,280 contracts at the end of 1994.3

A survey conducted by the Sydney Futures Exchange (SFE) and the Australian Investment Managers' Association (AIMA) of the use of derivatives by fund managers found that the SPI contract was the most widely used derivative product (SFE Survey (1994)). The SPI was used by 91% of the fund managers surveyed, compared to 88% who used the 10-year bond futures contract and 71% who used 90-day bank bill contracts. Few fund managers used other derivatives, such as forward rate agreements or swaps and options. Moreover, the fund managers indicated that they intended to increase their usage of the SPI contract during the following 12 months.

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3 Trading in futures continues to be a growth area. In May 1994 the SFE began trading futures contracts on three individual stocks (BHP, The News Corporation, and National Australia Bank). A further four stocks were added in September 1994 (BTR Nylex, MIM, Westpac and Western Mining. The SFE plans to increase trading in these individual contracts whilst the ASE plans to compete with the SFE by offering screen trading in futures contracts through SEATS.
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<td>4,800,846</td>
<td>6,839,450</td>
<td>10,439,735</td>
<td>10,206,607</td>
<td>10,755,618</td>
<td>15,729,728</td>
<td>19,121,256</td>
<td>28,795,938</td>
</tr>
</tbody>
</table>

| OPTIONS CONTRACTS |            |            |            |            |            |            |            |            |            |            |            |            |            |            |            |
| All Ords SPI    | 0          | 0          | 0          | 0          | 0          | 0          | 3,720      | 27,091     | 137,078    | 82,775     | 139,834    | 185,991    | 247,982    | 154,149    | 466,896    | 874,173    |
| Fifty Leaders SPI | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 11         |
| 90-Day Bills    | 0          | 0          | 0          | 0          | 0          | 0          | 13,024     | 31,633     | 58,033     | 193,291    | 515,119    | 605,641    | 719,482    | 610,458    | 663,317    | 919,697    |
| 3-Yr Bonds      | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 0          | 11         |
| 10-Yr Bonds     | 0          | 0          | 0          | 0          | 0          | 0          | 6,249      | 183,197    | 373,416    | 731,848    | 708,970    | 511,555    | 669,623    | 745,994    | 712,686    | 837,609    |
| Delisted Contracts | 0          | 0          | 0          | 0          | 0          | 0          | 390        | 1,993      | 2,641      | 12         | 0          | 0          | 0          | 0          | 0          | 0          |
| Total Options   | 0          | 0          | 0          | 0          | 0          | 0          | 23,383     | 243,914    | 568,527    | 1,029,571  | 1,389,048  | 1,378,569  | 1,743,884  | 1,827,957  | 2,359,840  | 3,165,758  |

Total Exchange  617,802  454,202  410,294  489,579  517,498  1,223,335  3,391,856  5,369,373  7,869,021  11,828,783  11,585,176  12,499,502  17,557,685  21,481,096  31,961,696

Source: Sydney Futures Exchange Information Department
1.2.1 The Index Futures Contract

A futures contract is a marketable forward contract. It commits the participant to buy (long) or sell (short) either commodities or financial assets at a specified time in the future. In practice futures contracts do not exist between individuals; they exist between the buyer and the futures exchange and the seller and the futures exchange through its representative, the clearing house. The clearing house monitors each contract (open position), and credits gains and debits losses to individual holders on a daily basis.\(^4\) To ensure daily adjustments, the clearing house makes 'margin calls' requiring participants to continually maintain deposits - in the form of cash or bonds - with the clearing house. These margin deposits are in addition to initial deposits of around 5% of the face value of the contract, which are varied by the clearing house to account for market conditions and price volatility. Contract holders can close out open positions by novation (if A holds a long (short) contract with B he cancels his position with a short (long) contract with C), by delivery of the underlying asset (some commodity futures only), or by cash settlement at expiration.

A futures contract written on a portfolio of common stocks is called a share price index futures contract. Index futures in Australia are based on the Australian Stock Exchange's All Ordinaries Index (AOI). The contract unit of an index futures is equal to twenty five times the AOI. So, if the AOI stood at say 2000 the contract value would be $50,000. If a trader was long at this price and the index moved to 2010, then he would show an unrealised profit of $250. But if the index fell to 1990, then a loss of $250 would be incurred. The converse will hold for a short position.

The AOI futures contract is currently available at three monthly intervals. Trading is terminated at 1200 noon on the second last business day of the settlement months June, September, December and March. There is no physical delivery - open positions are settled with cash on the business day following close of trading.

\(^4\) This procedure is referred to as 'marking to market'.

1.2.2 Economic Benefits of Futures Contracts

The growth in futures markets is traditionally justified and associated with such economic functions as: transaction cost advantages, intertemporal price discovery, risk hedging and information exchange. The economic benefits of futures contracts are now reviewed.

**Transaction Costs**

Futures contracts have a transaction cost advantage over the direct purchase of the security or commodity and forward contracts [Brons (1991)]. Brokerage commissions are lower in futures markets, the open outcry system and high trading volumes result in higher liquidity, and there are no restrictions on short selling. Further, the stock market consists of a collection of diverse individual stocks which are more likely to react only to firm specific information which in turn reduces market transparency and inhibits trading. Futures contracts also reduce search, liquidity, and moral hazard costs [Cagan (1981) Jaffe (1984) and Veljanovski (1986)]. This allows managers and other investors to either diversify or increase market risk easily and at low cost [Figlewski and Kon (1982)]. Futures trading also requires less capital. Trading can be initiated by posting only an initial margin which enables investors to trade on accessible credit. Margins vary as a percentage of the contract but, in general, they are less than 5%. Whilst positions are also marked-to-market on a daily basis, the net effect (except for extreme changes) is an advantage for traders over arranging credit for direct leverage purposes [Jaffe (1984)].

**Information Role**

Grossman (1977) argues the role of a futures market as a place where information is exchanged, and where people who collect and analyse information about the future state of the world can earn a return on their investment in information gathering. This is related to the fact that it is transactionally less costly to trade on information in futures markets. Futures markets, therefore, act as a conduit to conduct information from the informed to the uninformed. Because information is costly to gather and diagnose, this creates noise in the price system and prevents informed views about the future being
instantaneously and clearly revealed. These factors (i) provide the opportunity to earn an economic return on information gathering, (ii) explain why futures markets may reflect information faster than equity markets, (iii) suggest a process whereby information is disseminated across markets, and (iv) offer one explanation as to why markets are not always perfectly arbitraged when information is costly.

It is further argued that the introduction of derivative securities, such as futures markets, always lowers the mean and variance of spot price movements [(Peck (1976), Turnovksy (1979) Campbell and Turnovsky (1982)], in terms of the information role these markets provide. They become a centralised clearing house for information; collecting, analysing and disseminating the collective beliefs of all market traders. This activity provides an externality for cash market participants, who can base their current hedging and purchase decisions on this extra information. According to Powers (1970) and Cox (1976) that leads to intertemporal smoother and more efficient resource usage.

The informational role of futures proposed by Grossman is exacerbated with the use of index futures. Trading in the index futures market is based upon the index as a whole and because of the institutional features which make trading in futures more transactionally efficient, it is hypothesised that macro information should flow more quickly into futures prices. Grossman (1988) further argues that the prices of index futures contracts convey important information about the costs of insurance strategies. If futures trading is restricted, then large institutional managers will be forced to use synthetic strategies (by combining cash securities) to insulate the value of portfolio holdings. Hence, portfolio insurers will not know the cost (either actual or opportunity) of these strategies when they do not know the intensity with which other investors are using similar strategies. Further, in the absence of an index futures market, if a substantial number of investors suddenly decide to use synthetic insurance strategies predicated on historical sharemarket volatility, then the increased trading volume may increase cash stock market volatility.
Diversified Portfolios and Index Futures

Stock indexes can play an important part in managing share portfolios. This principle has become widely understood during the last thirty years with the dissemination of theories from modern finance and portfolio analysis. Prior to that time, stock exchange indices were mainly used as descriptive and comparative measures of stock market performance. Before Markowitz (1952), Sharp (1964), Litner (1965) and others, it would have been improbable that optimal properties might be associated with stock index portfolios. It is thus valuable to briefly review the elements in finance theory which give the motivation for investors to place a high value on opportunities to purchase a well diversified portfolio and its extension into index futures.

A diversified portfolio, by eliminating asset or security specific risk, returns a higher ratio of expected return to risk than can be achieved by allocating a high proportion of the portfolio to any individual security or to a small number of securities. Furthermore, if capital markets are efficient, then the only decision to be taken in determining a portfolio is the amount of risk to be borne. Deciding the amount of risk is the key decision because 'separation theory' states that the optimal portfolio is always the market portfolio and this portfolio should be held by all investors. Trading or speculative strategies are not optimal. The investor can regulate the amount of desirable risk associated with the optimal portfolio by combining it with a risk free investment, such as Treasury bills or government securities, to reduce risk, or by purchasing the market portfolio on margin to lever up risk. As the market portfolio is rarely observable the share market stock index is often used as a surrogate. These propositions can be presented in the form of 'mutual fund' theorems. Their development has caused institutions and other investors to become interested in diversified mutual funds generally, and in the formation of index funds that provide a portfolio corresponding directly to the components of the AOI, specifically.

A major problem with an index mutual fund is that it is difficult and costly to maintain the portfolio that corresponds fully to the specified index. As the prices of individual securities change, and contributor funds flow in and out, the portfolio manager must
make appropriate adjustments in each of the component stocks. Transaction costs, and trading in potentially thin markets, make this process expensive. If the portfolio manager attempts to minimise transaction costs by approximating the results of the index then the actual returns may deviate substantially from those of the index. This would especially occur when a small number of stocks were held and the statistical inter-relationships were unstable. Another problem is that index funds may not be easily purchased on margin. An investor who is dissatisfied with the expected risk/return ratio of an index fund can bear a higher amount of risk by borrowing from traditional sources of credit. But again, this could be expensive in both transaction and search costs.

Finance theory indicates the need for investment securities that allow investors to participate fully in the market, and provide flexibility to achieve a levered long position as well as hedged short positions. Mutual funds conceptually provide this vehicle, but they are costly to monitor and have limited flexibility because of higher transaction costs, lower liquidity and limited ex-ante hedging attributes. A derivative security of the stock index, such as the index futures contract, provides an efficient and flexible vehicle as well as a further ex-ante dimension to manage and fine tune portfolios.

1.3 OUTLINE OF THE THESIS
The following section outlines the content of the thesis in more detail and provides a background and a justification for each chapter.

1.3.1 Information and Microstructures
One area of intense interest to financial economists concerns the path of the reaction of security prices to information. The litany of research aimed at determining the 'informational efficiency' of security markets over the last thirty years bears testimony to the belief in its importance by many accounting and finance researchers. But precisely how information affects the beliefs of market participants and how information is disseminated into prices, is not well understood.
There is also a body of empirical research which has documented the existence of seasonalties or predictable price reactions in security markets. For example, a widely documented but unexplained anomaly is the negative Monday day-of-the-week return effect first identified by French (1980) and Gibbons and Hess (1981). Chiang and Tapley (1983) extended this research to a wide set of futures commodities and found that the day-of-the-week effect differs between cash and futures markets. In more recent years, with the increased availability of finer data sets, research by Wood, McInish and Ord (1985), Harris (1986), McInish and Wood (1991) and Ekman (1992) amongst others, have concentrated on the intraday return and volatility patterns in stock and futures markets. It was found that there is a consistent U-shaped pattern, with positive returns together with higher volatility and trading volume observed near the open and close of trading.

One potential explanation for this pattern is the impact of new information. The issue has been examined from a wide ambit of perspectives. Explanations range from the cognitive psychology view which suggests that investors tend to overweight the value of current information, noise traders who follow self-fulfilling fads not related to information, positive information spillovers, asymmetric information impacts; through to the contention that prices vary rationally through time in a fashion that is consistent with time varying risk premiums, and the arrival of public and private information.

A number of other factors have also been put forward as explanations of these trading patterns including: (i) opening price setting mechanisms such as call auctions; (ii) trading procedures such as open outcry versus electronic trading; (iii) quote driven versus order driven price setting; (iv) non-synchronous trading in thin stocks on intraday indices; (v) speculative activity which is attracted to specific markets; (vi) sample specific and/or market specific anomalies; and (vii) other trading microstructures such as extended trading hours and trading halts.

The finer analysis applied by the microstructure research programs offers the prospect of a more in-depth understanding of the 'beehive' like activity of markets. The availability
of futures markets introduces a further dimension to these microstructure studies. It leads to several complicating factors, and provides an intensified opportunity to research financial markets. For example, a comparison of the intraday price evolution in both cash and futures prices is useful in that it allows some control over the different microstructure effects in these two related, but separate markets. This is important because price evolution over the day may depend upon different attributes such as trading mechanisms and structures, heterogeneous trading clientele (dealers, private traders, hedgers and speculators), or different information flows over the trading period. These and other frictions are departures from perfect market assumptions usually made in capital market research and are possible explanations for documented price deviations from what we might expect under idealised assumptions.

Chapter two provides a summary of the theoretical arguments which might explain the occurrence of patterns in returns, volatility and trading volumes in stock and futures markets and some of the possible deviations between the two markets. The summary in chapter two concentrates on information theories and microstructure theories and is prefaced by an overview of the Australian trading environment. In chapter three the empirical research on interday and intraday patterns in returns, volatility and trading volumes is reviewed. This chapter forms the primary motivation and much of the empirical background for the analysis undertaken in the later chapters.

### 1.3.2 Intraday Returns, Volatility and Trading Volume

Chapters four, five and six analyse intraday returns, trading volume and volatility. These chapters analyse the impact of overnight information from the US stock market. If markets are sufficiently integrated such information impacts should occur simultaneously across international markets, but when the market is closed then the impact is accrued and occurs at the opening of trading the next day. Further, a number of researchers [Harris (1986), Amihud and Mendelson (1987, 1990, 1991a, 1991b)] have suggested that accrued overnight information is a major cause of the unusual activity at the opening of
trading. Therefore, chapters four, five and seven specifically analyse the impact of accrued overnight information on the opening price returns, price volatility and trading volume of the AOI cash index and SPI futures, and describe the subsequent intraday evolution of those variables.

The Australian cash stock and futures markets provides a case study opportunity to extend the research on the effects of information, microstructures and the international transfer of information across international markets for a number of reasons. The Australian markets are much smaller in size and the cash stock market has a pronounced nonsynchronous trading problem induced by thin trading conditions. The extension of the intraday research to the smaller Australian market is important because prior studies, which used data from the New York Stock and Futures Exchanges and the Tokyo Stock Exchange indices, are more representative of relatively large firms and high relative trading frequency and market depth. Harris (1986) and others have reported that interday and intraday price and volume patterns vary according to firm size and trading depth, with significant differences obtained over trading and nontrading periods. The comparison with the smaller Australian market should throw some light on whether previously observed patterns are market specific or caused by specific information or structural effects.

Secondly, the Australian market to a greater extent than the major stock and futures markets, is dependent on international information. The Australian economy depends on international commodity prices and manufacturing activity for much of its public macro information, and is relatively small and a price follower. In particular, the Australian market does not have an overlap in trading times with the US market and this is an important consideration for traders in the Pacific-Asian economic zone. It may also enable a cleaner analysis to be undertaken of the impact of public information on opening prices.

Thirdly, Australian stock and futures and markets have a number of unique trading mechanisms. They range from lagged opening price setting mechanisms and screen
quoted order driven price setting in the stock market; to overnight trading, lunchtime closing and earlier opening and later closing in the futures market. These features provide the opportunity to compare the effects of trading halts and market mechanisms across markets in the spirit of Gerety and Mulherin (1992) and Amihud and Mendelson (1987, 1991a, 1991b).

The analysis applied in these chapters also extends empirical research in several new directions. By comparing the processes in both markets it attempts to establish whether patterns persist in the cash market contemporaneously with the futures market. A comparison of these two associated markets would also be useful in filtering out the effects of different microstructures on prices. Superficially, a number of information and structural effects should lead to differential price impacts in these two separate markets. Any observed deviations from expectations have important implications for hedging and trading strategies in both markets. Secondly, intraday 15-minute observations are used in the analysis which makes this one of the first microstructure studies of stock index futures in Australia. The methodological approach of using finer trading intervals will more likely help to identify the micro level relations and may help in the debate about the causal effects of trading patterns. Finally, this thesis applies intervention and transfer function time series models to analyse the impact of overnight information at the opening of the market and over the course of the trading day. The advantage of this approach is that it allows for the incorporation of the effects of information interventions and the modelling process is flexible - the transfer function can be specified to capture the effects on the time series in a variety of ways. For example, step functions, pulse functions, or oscillating impact functions may be used to test for immediate impounding, decaying reaction or overreaction to information. The use of transfer function time series models, therefore, represents an innovative approach to statistical modelling which has rarely been applied to financial markets.

The issues of price return, trading volume and volatility overreaction is particularly relevant in futures markets. Since one of the theoretical economic advantages of futures
prices is to provide an information discovery role, the speed and nature of futures price adjustments suggest important economic welfare and externality considerations. In particular, the design and the justification of margin requirements and position limits appear to rely on the assumption that futures markets overreact to information in the short run [Ma, Dare and Donaldson (1990)]. However, frequent changes in margin requirements and position limits to control default risk may only translate into lower liquidity and higher transaction costs which may reduce the rate of information dissemination. Further, the tendency of the market to overreact/underreact to information or for there to be deterministic price spikes throughout the trading day has implications for traders. If prices overreact to information and spillovers occur, contrarian strategies may prove profitable, or if prices under react to information then a policy of 'jumping on the bandwagon' could prove successful.

1.3.3 Arbitrage and Intermarket Volatility
The introduction of futures trading also allows arbitrage strategies to be traded between spot and futures markets - a natural extension being program trading - and has generally increased the availability of a wide range of both insurance and speculative strategies. This provides the opportunity to test empirical questions such as whether index arbitrage reinforces the informational link between the two markets and provides a countervailing influence on any differential information or microstructure effects, or whether the price effects from the more highly levered and speculative participants in the futures market are transferred across to the cash market. These issues have practical importance to participants in security markets and are currently the focus of policy debate in the US and Australia [USGAO (1994), ASC (1994)]. Chapters seven, eight and nine engage a number of these issues. Chapter seven tests whether the introduction of derivative futures markets trading has had an impact on the longer term volatility in the underlying stock market. Chapters eight and nine analyse the arbitrage relationship between the cash and futures markets. An outline and motivation for these chapters follows.
Increased Volatility in the AOI Cash Market

One accusation often levelled against derivative markets is that they increase the volatility of cash markets via speculation in the overlying futures markets. Speculative activity is said to increase price variability - not in the desirable sense of reflecting the underlying volatility of actual economic conditions - but in the undesirable sense that if speculation were constrained, then the variability of cash prices would be less without adversely affecting the allocation of resources. The higher volatility in the derivative market is then transferred across into the underlying cash market by the process of arbitrage. The advent of screen trading in Australia over the last few years has made arbitrage more accessible and cost effective.

There are two viewpoints on the impact of cash/futures arbitrage. The stabilising hypothesis argues that the introduction of derivative securities, such as futures markets, always lowers the mean and variance of spot price movements [Peck (1976), Campbell and Turnovsky (1982)], because of the efficient informational role these markets provide. They become a centralised clearing house for information, collecting analysing and disseminating the collective beliefs of all market traders. This activity also provides an externality for cash market participants, who can base their current hedging and purchase decisions on this extra information, which in turn leads to intertemporal smoother and more efficient resource usage [Powers (1970), Cox (1976)]. As a consequence, it is argued that if cash markets are more volatile, the reason must be that spot prices have become more sensitive and responsive to actual market conditions!

The destabilisation counterargument proposes that excess volatility might be caused by amateur speculators who lose money, retire, and are continually replaced by others equally inept [Kaldor (1939)]. Further, Baumol (1957), hypothesised that speculators buy or sell only after a price movement has started, which accelerates price trends and causes prices to be more volatile. If speculation tends to increase price variability, derivative futures markets, which make speculative trading inexpensive through low
margin costs, would act to increase the volatility of cash markets through arbitrage and other activities.

Potentially the research question of whether the introduction of derivative trading increases cash market volatility is important because it could have repercussions in a number of critical areas in the economy. Increased stock market volatility may increase real interest rates and the cost of capital, leading to a reduction in the value of investments and loss of confidence in the stock market. In the extreme, stock markets may even become the province of speculators and insiders, rather than rational long term investors. This issue may be even more critical to the Australian economy because of the thinness of the market and the possibility that it may be dominated by a small number of large traders.

These stabilising/destabilising propositions are examined in chapter seven by using six years of daily closing price data from the AOI, around the introduction of SPI index futures trading on 17 February 1983 and index futures options on 18 June 1985. This data set enabled approximately two years to be analysed before and after each intervention in order to ascertain the long run impact of derivative futures trading on the AOI [Edwards (1988b)]. The equality of variances are tested after fitting appropriate time series models to the various pre and post data series [Priestly (1981)].

1.3.4 Mispricing and Mean Reversion

It is well known that the availability of an underlying basket of shares and a futures contract written on those shares, provides an arbitrage link between these markets. The effectiveness of the link will be dictated by a number of factors including the efficiency and expectations of participants in the market, transaction costs, and the availability of arbitrage capital.
**Mispricings**

Some considerable research has focused on stock index arbitrage strategies and the documentation of deviations from ‘fair values’. In an efficient market there should be no evidence of sustained arbitrage mispricing or any structural dependence in the mispricing series - the path of the mispricing series should fluctuate randomly around zero. The empirical observations have contrasted sharply with theoretical expectations. Researchers who used interday closing price data reported substantial and sustained mispricing between the cash index and futures markets. For example; Cornell and French (1983), Figlewski (1984) Arditti, Ayadin, Mattu and Rigskee (1986) *in the US*, Bowers and Twite (1985) *in Australia*, Brenner, Subrahmanyam and Uno (1989) *in Japan*, and Yadav and Pope (1990) *in the UK*. One possible reason for the observed mispricings is that stock and futures markets do not have contemporaneous closing times. This has been the case with previous research in Australia which has utilised end of day non-contemporaneous closing prices to calculate the mispricing series.

More recent research has used intraday transaction data to obtain a contemporaneous arbitrage price and to undertake a micro level analysis of the evolution of the mispricing series. This research has found that: intraday arbitrage mispricing still remains (even after allowing for execution lags); there is strong and persistent positive autocorrelation in mispricing, and negative autocorrelation in the first difference of the mispricing series [MacKinlay and Ramaswamy (1988), Brennan and Schwartz (1990)]. Also, there is some evidence that the degree of mispricing may vary between different markets or structures [Chung (1991), Lim (1992), Ho, Fang and Woo (1992)]. Such findings of sustained wave like mispricing indicate the availability of arbitrage profits and are not consistent with the hypothesis of market efficiency.

The above research, however, has largely ignored the impact of specific information flows or the widely differing microstructures of the stock and futures markets on the mispricing series. Such dependencies in the index futures mispricing series may be influenced by the microstructure of the futures market and the stock market. As has
already been documented the stock and futures markets differ in their methods of trading with different opening price setting mechanisms, trading times, and the possibility that each market may be reacting to different information sets. In Australia, the actions of arbitrageurs serve to link together two very structurally different markets.

Chapter eight seeks to bridge some of the gaps in the empirical literature in Australia. The first contribution made is to document the intraday mispricing series using high frequency and contemporaneous intraday data from the Australian market. The second contribution is to analyse the impact of overnight information on the opening arbitrage price and the effect over subsequent intraday arbitrage pricing. This is achieved by extending the transfer function time series model first developed in chapter four. Such an analysis is designed to determine whether there are statistically significant patterns in intraday mispricing, and whether observed patterns are related to structural or informational features or, indeed, if the actions of arbitrageurs overcome the nuances of individual markets.

Mean Reversion

In a mean reversion process, prices are expected to change back toward a 'fundamental mean value' whenever market forces push the price sufficiently far from that value. If prices are 'strongly mean reverting', then once prices depart from fundamental value they return to that level very quickly - this implies a high response supply elasticity of traders who trade on price deviations. On the other hand if prices are 'weakly mean reverting' this implies a low response elasticity or evidence that the activities of noise traders are still influential. In a well functioning and competitive price market one would expect any deviations from fundamental value to be eliminated fairly quickly by the actions of arbitrage price traders.

Chapter nine tests the existence of mean reversion in the mispricing series in the Australian market. Mean reversion is defined as the existence of a negative relationship between changes in mispricing and the level of mispricing in the previous period [Yadav and Pope (1993a)]. The extension of this research to Australia is important because of
the different trading structures, especially the fact that there is a high amount of infrequent trading in the underlying stocks which constitute the AOI. The infrequent trading argument underlies the debate in the literature that mean reversion is a 'statistical illusion'.

A second contribution of chapter nine is to provide empirical evidence on how the mean reversion parameter may vary with microstructural or market induced factors. The rational information models of Kyle (1985) and Admati and Pfleiderer (1988) predict that rational arbitrage induced traders would be more active at the open and close of trading; whilst the noise trading models of Shiller (1986), DeBont and Thaler (1985, 1987) and Poterba and Summers (1988) predict that the excess trading of speculators would overcome the actions of arbitrageurs in periods of high volume. Vaidyanathan and Krehbiel (1992) provide a further scenario by suggesting that arbitrage activity between markets with structural differences causes fluctuations in the mispricing series, and that increasing the strength of arbitrage, serves to increase the fluctuations. Yadav and Pope (1993a) analysed the behaviour of the mean reversion parameter as a function of the level of mispricing, time to maturity of the futures contract, day of the week and hour of the day. This microstructure research on mean reversion is replicated and extended in chapter nine.

1.4 SUMMARY

This chapter has provided the motivation for this thesis and outlined the contributions to be made. The background and increased trading volume in derivatives traded on the Sydney Futures Exchange was documented. An outline of the chapters in the thesis and a brief justification was also provided. The next two chapters now provide more specific and essential background for the remainder of the thesis. Chapter two examines the potential impact of information and microstructures on markets and chapter three provides a review of a number of empirical studies.
2.1 INTRODUCTION

The impact of information and trading structures on prices and trading volume is a growing area of academic research. As mentioned in chapter one, a number of empirical studies have documented the existence of persistent interday and intraday patterns in equity and futures markets, particularly in the US. French and Roll (1986) first observed that the hourly trading time variance of US stock returns was up to seventy times greater than non-trading time variances, and suggested that higher trading time volatility could be explained by: 1) public information which accrues overnight and during the trading day but is only incorporated into prices during trading times; 2) private information which arrives randomly over the course of the trading day and incorporated into prices before closure; or 3) by noise trading. Since the French and Roll study a number of theories have emerged which seek to explain these patterns in terms of the flow of information over the trading day. These information theories are reviewed in this chapter under the general headings of rational information theories, noise trading theories, and information and trading volume.

One other important factor that may affect prices and trading volume in security markets is the microstructure of the market or the trading procedures or practices. The recent research of Amihud and Mendelson (1987, 1990, 1991a, 1991b) has been instrumental in highlighting and examining the effects of the dealership market versus the call auction
procedure. Further, a number of other factors have also been put forward as explanations of intraday patterns including: (i) trading procedures such as open outcry versus electronic trading; (ii) quote driven versus order driven price setting; (iii) non-synchronous trading in thin stocks on intraday indices; (iv) speculative activity which is attracted to specific markets; (v) bid-ask bounce (vi) sample specific and/or market specific anomalies; (vii) other trading microstructures such as extended trading hours and trading halts; and (viii) various spillover and feedback influences between cash and futures markets including arbitrage motivated program trading and volatility spillover.

The purpose of this chapter is to provide a theoretical outline of the explanations which have been proposed for the observed price, volatility and trading volume patterns over the course of a trading day and during trading and non-trading periods. The review mainly encompasses information and trading structure explanations, but also highlights the differences (and similarities) between stock and futures markets and describes the Australian trading environment. Chapter three provides an overview of the relevant empirical research. In this manner chapters two and three provide much of the background to chapters four, five, six and seven and an input into the later chapters eight and nine. The reviews contained in chapters two and three are supplemented by drawing upon further research in each chapter to reinforce particular arguments or to provide additional background.

Chapter two is organised as follows. Section 2.2 outlines the trading environment in Australia and the importance of comparing futures and stock markets. Sections 2.3, 2.4 and 2.5 provide a more detailed overview of information theories, the trading environment and other microstructure issues. Section 2.6 concludes the chapter and provides a schema which visually displays and summarises the potential impacts on the individual stock and futures markets, and the spillover and feedback effects between the markets.
2.2 THE AUSTRALIAN ENVIRONMENT

This section provides an overview of the importance of studying the Australian security markets and the comparison between stock and futures markets.

2.2.1 The Australian Stock and Futures Markets

The Stock Market

The small internationally dependent Australian stock market provides an excellent case study for investigating the effects of particular market microstructures, mechanisms and information flows on price volatility because of several unique institutional and trading factors. The Australian Stock Exchange (ASE) has recently introduced a stock exchange automated trading system (SEATS), whereby all trading is order driven and fully computerised.\(^1\) Trading in the ASE used to occur over two sessions within the day before the introduction of automated trading. The morning trading session used to open from 1000 to 1215, close for lunch until 1400, and then traded in the afternoon until 1515. In October 1987 the ASE began moving from a manually processed open outcry system to a fully computerised trading regime. The changeover to SEATS was completed in September 1990 when the midday break was eliminated and trading hours extended through to 1600. The Australian stock market now trades continuously from 1000 to 1600, although, trading can be extended in special circumstances.

SEATS operates an order driven price setting mechanism through a series of interconnected terminals that are located principally in brokers offices. The system allows brokers to observe the real time market for each listed security and to amend existing orders or enter new orders. The SEATS screen provides for each traded stock a range of information; for example, each unfilled order's broker identification number, the order price, and the order quantity if the order does not exceed $10,000. The system provides a path for broker to broker contact, whereby negotiations to trade can be conducted in privacy. One proposed advantage of SEATS is that it provides accessible information in

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\(^1\) Australia was the first fully consolidated stock market in the world.
a controlled environment: '...(SEATS) has transformed the sharemarket by taking it from the hectic floor onto screens in stockbrokers offices. This new technology gives complete control. It provides easily accessible information. Stockbrokers can observe the market and concentrate on making responsive decisions.' [ASE information pamphlet (1993)].

The SEATS system sets prices by initially posting buy and sell quotes into the order book section of the computer. Before accepting a transaction the broker can scan information on 'buyers' and 'sellers' as well as accessing a rundown on how the stock has traded over the course of the day. As well as the stated advantage that it takes trading away from the hectic floor and allows brokers to make responsible decisions from easily accessible information, the system greatly increases the speed at which trading takes place. Furthermore, ASE rule 2.5 requires SEATS operators to ensure the conduct of an orderly market. Overall the SEATS system differs significantly to the specialist quote driven system used in the US stock market and therefore offers the opportunity to analyse information and price impacts in a different microstructure setting.

Australia also has a unique opening price setting mechanism. Most other stock exchanges set opening prices with a clearing transaction dominated by quote driven market makers. Thereafter, prices are determined in a continuous market. In Australia, special priority trading rules are applied to the opening of the ASE, whereby the normal continuous auction procedure is suspended and prices are set by matching prior bids and offers during the first nine minutes of trading (see Appendix 2.1 for a complete description). This staggered opening procedure represents a suspension of trading and enables a comparison to be made with other exchanges in the spirit of Amihud and Mendelson

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2 The prior bids and offers are determined in the pre-opening mode from 0730 to 1000. Surviving bids and offers are reinstated from the prior trading session, which in turn can be deleted or amended and new bids and offers added.
(1987) who argue that opening price setting mechanisms will affect the volatility and structure of prices.\(^3\)

Another factor is the international trading times and the nature of the Australian market. First, the US stock market has been found, by far, to be the most influential market in the world and US price movements have important 'information' content that influence other domestic stock markets [Eun and Shim (1989), Bailey (1990), Park and Fatemi (1991)]. Secondly, the Australian economy depends on international commodity prices and manufacturing activity for much of its public macro information, is relatively small and a price follower, and trading times do not overlap the US market. This means that publicly available overnight information can be isolated and the effects more rigorously analysed.

In this regard there have been a number of hypotheses put forward to explain the higher mean returns, volatility and trading volume at the opening of a market. They range from accrued overnight public information, private information released at the close on the previous day, the opening price setting mechanism [Amihud and Mendelson (1987, 1991a, 1991b), Stoll and Whaley (1990b)], specialists attempts to maintain price continuity [Miller (1988)] and speculative activity. The unique features of the Australian market more easily allow the impact from overnight information to be isolated and the impact on opening prices analysed. The dissemination of information into opening prices is a major focus of this thesis. Further, the Australian market is an order driven market not a specialist quote driven market as in the NYSE and this provides the opportunity to examine market behaviour in a different structural setting.

A further feature is the degree of nonsynchronous trading or the thinness of the Australian stock market. The AOI is a broadly based stock index containing some 250 stocks. By international standards the Australian stock market is very thin with many stocks not trading consistently every day.\(^4\) The greater the non-trading of stocks in the AOI, the

\(^3\) Another microstructural feature in the Australian stock market is that trading is halted for ten minutes at the time of release of 'price sensitive' information. This is not the case in derivative markets and offers a number of research opportunities.

\(^4\) Research by Hathaway (1986) indicated that less than 30 stocks traded consistently every day.
more it represents an average of stale historical prices (usually detected by positive first order autocorrelation in price changes), rather than current prices. This factor may induce differences in the reaction times of cash indices to new information and cause the AOI to be less volatile than it would be if it reflected current prices. Regardless, the impact of thin trading must be controlled by constructing an appropriate statistical model to take account of the lagged dependency structure in the data.

In summary, previous research has concentrated on larger well traded markets and the extension into the smaller Australian market provides the opportunity to examine the effects of different trading structures and information on price formation under thinly traded conditions. The extension is important because previous studies using data from the New York Stock and Futures Exchanges and the Tokyo Stock Exchange is more representative of medium and large firms. Further, Harris (1986), Foster and Viswanathan (1989, p.6), and Stoll and Whaley (1990b, p.58) have reported that interday and intraday price patterns vary according to firm size, with significant differences obtained over trading and nontrading periods. The comparison with the smaller Australian market should determine whether previously observed patterns are market specific or caused by specific information and/or structural effects.

*The Futures Markets*

The decision to study intraday price formation reinforces the importance of also focusing on futures markets because of a number of reasons related to microstructure and information feedback. Firstly, in contrast to the stock market, the futures market is a clearing open outcry auction market from opening to closing - the futures market employs a uniform market structure. Thus, a comparison between stock and futures markets is a useful technique to compare the effects of market structure on intraday price formation. Secondly, if there are 'frictions', such as transaction costs and nonsynchronous trading in smaller thinly traded stocks, cash index prices will be slow to adjust to new information and this can induce spurious first-order autocorrelation in stock returns. Conversely, changes in index futures prices should have lower autocorrelation because they have a
comparative advantage in transaction and liquidity costs [see for example Silber (1984), Veljanovski (1986), Berkowitz, Logue and Noser (1988)]. These transaction and liquidity advantages arise because:

(i) brokerage commissions are much lower in the futures market;
(ii) the open outcry system and higher trading volume in the futures market results in lower liquidity costs;
(iii) futures trading requires much less capital;
(iv) futures markets have no restrictions on short selling; and
(v) futures markets reduce search and moral hazard costs.

Thirdly, a number of theoretical studies have also differentiated between the types of information that flow to cash stock and index futures markets. For example, Kumar and Seppi (1989), Chan (1990), and Subrahmanyam (1991) showed that fixed costs of trading, budget constraints, and different expected profits caused traders in futures markets to collect more market wide information and traders in cash markets to collect more firm specific information. Finally, infrequent trading of stocks composing the AOI means that the computed index value will incorporate some prices which are stale. Besides infrequent trading individual security returns may be influenced by the splitting of large buy and sell orders into two or more smaller orders. This is more likely to occur in smaller markets where participants have monopoly power or access to insider information.

The above arguments suggest that there may not be a unidirectional relationship in price innovations because of different trading structures and that cash and futures markets may not be equal in their capacity to disseminate information in prices. The preponderance of empirical evidence indicates that intraday stock index price changes are positively autocorrelated and futures price changes are negatively autocorrelated. This indicates that the primary microstructure effects are infrequent trading of index stocks and bid-ask bounce for futures.
As a final note, the microstructural differences between the futures and cash markets are much greater in Australian than in overseas markets. For example: the Australian stock market trades continuously throughout the day whilst the futures market halts trading for one-and-a-half hours over lunch; there is order driven computer based trading in stocks and open outcry trading in futures; there is overnight trading in futures but none in stocks; the futures opens 10-minutes earlier than the stock market with a different price setting mechanisms and closes 10-minutes later.

The next three sections outline in greater detail a number of information, microstructure and trading volume theories which may impact upon the evolution of intraday prices. The purpose in presenting this review is to provide a theoretical background for later chapters and a basis for the design of appropriate statistical tests to examine the these influences.

### 2.3 INFORMATION THEORIES

#### 2.3.1 Rational Theories

One negative heuristic held by a number of researchers in financial economics is that financial markets are 'efficient' in that prices reflect all available information. An extreme form of this efficient market hypothesis (EMH) implies that when a new piece of information becomes publicly available, it is instantaneously impounded into security prices. A lag in the price adjustment or a slow transfer of information into prices would not exist under this strict form of market efficiency. This approach assumes that traders will consistently calculate the price of a security over long time horizons and that short term speculators will have little influence in price formation.

The observation, however, that the clientele of markets range from short term speculators through to long term passive traders and the emphasis by professional traders on the prediction of near term changes in prices, is explained away by backward induction. Backward induction means that all traders have the same time horizon when deriving value. For example, if a speculator plans to sell in fifteen minutes then the expected price
at that time must be calculated. However, by backward induction that price depends on
the price in the next fifteen minutes, which in turn depends on the price in the next fifteen
minutes, and so on. By this process, no matter how short the holding period is, all
traders perform exactly the same present value calculation as the long term passive trader.
Prices are therefore unaffected by the time horizon as long as the discount rate and risk
functions remain constant. Under this strict interpretation of price formation most market
participants have homogeneous expectations, are economically rational and markets
competitive. If prices deviated from fundamental long term value or had 'memories' then
rationally competitive traders would quickly arbitrage away profits and guarantee that ex­
ante prices adjusted randomly in accordance with the unanticipated arrival of information.

Several models have related intraday patterns in prices and trading volume to asymmetric
information flows over the course of the trading day. Kyle (1985) provided an auction
model which specifies a relationship between private information, trading volume and
stock return volatility. In Kyle's model there are three classes of traders who are all risk
neutral: 1) Private information traders who trade rationally and strategically to maximise
profits and who utilise an information set generally not observed by the market; 2) Random liquidity traders whose trading is determined exogenously by random factors
unrelated to information about future prices; and 3) Specialists or market makers who
have no private information but who fill the orders of the other two types of traders.
Market makers cannot distinguish between informed and uninformed trading and only
observe total order flow. They are competitive, risk neutral and earn zero net profits. In
Kyle's model, private information is reflected in prices at a constant rate per trading hour,
and price innovations are only affected by the trading volume of random liquidity traders.

Admati and Pfleiderer (1988) extended the model of Kyle by including a fourth class of
traders - discretionary liquidity traders. These traders do not have private information but
have some discretion over the timing of their trading activity along with private
information traders. The motivation behind the Admati and Pfleiderer model is to explain
the U-shaped patterns in price innovations and trading volume observed in empirical
studies. The model predicts that discretionary liquidity trades will be concentrated and take place as close as possible to the realisation of liquidity demands; and private information traders will prefer to trade when the market is thick in an attempt to disguise the private information released by their trading. Moreover, further clustering of trading occurs because private information traders will reveal enough incremental information to make trading by uninformed traders profitable. Consequently, both informed and uninformed choose rationally to trade simultaneously.

Admati and Pfleiderer therefore hypothesised that the empirically observed U-shaped patterns were rationally related to trading structures, information flows and the trading clientele of the market. For example, the act of opening and closing a market forces an increase in non-discretionary liquidity trading which, in turn, attracts private information and discretionary liquidity traders. Further, information traders who trade on public information released over the non-trading hours, are more active at the opening of trading; whilst private information traders, who gather information during the trading day, are more active towards the close of trading. The combination of these effects will result in increased activity in financial markets at the opening and closing of trading, with the increased volatility of returns being interpreted as a rational (but noisy) signal for the information of informed traders and is associated with trading volume.

Campbell and Hentschel (1992) contend that information arrival has an asymmetric effect on volatility between large and small pieces of news, and good and bad news. If the arrival of large pieces of good news is persistent (large pieces of good news are followed by other large pieces of good news), this increases future expected volatility, which in turn increases the required rate of return and lowers the stock price, dampening the positive impact of the good news. On the other hand, a large piece of bad news increases volatility, raises the required rate of return and amplifies the negative impact of the bad news. In contrast, the arrival of a small piece of news lowers future expected volatility.

In order to realise the value of private information before it decays and becomes public over the overnight non-trading period
and increases the stock price. In the extreme case in which no news arrives, the market rises because 'no news is good news' about future volatility. Campbell and Hentschel (1992) argued that this 'volatility feedback' can explain why large negative stock returns are more common than large positive returns, and why excess kurtosis is observed in many stock return series.

2.3.2 Noise Trading Theories

The possibility that price deviations away from some 'fundamental value' and excess volatility is caused by the overreaction of traders to each other's trading which may be driven by psychological factors brought on by the actions of speculators and 'day traders', is discussed by a number of researchers. For example, the October 1987 sharemarket crash has been interpreted as the breaking of a speculative bubble [Stiglitz (1990)]; White (1990) provides arguments that the boom and bust of the 1920's was mainly driven by speculative elements; and De Bont and Thaler (1985, 1987) and Pettergill and Jordan (1990) contend that investors overreact to current information. The 'overreaction hypothesis' is based on the belief that market participants tend to overweight recent information and underweight prior information when revising their expectations. DeBondt and Thaler (1989) state that market overreaction: 'typifies very precisely the excessive reaction to current information which seems to characterize all the securities and futures markets.' DeBondt and Thaler (1989) provide a summary of empirical evidence of contrarian strategies which are successful because of systematic investor overreaction.

The actions of speculators (or noise traders) are seen to affect markets in a number of other ways. For example, amateur speculators are continuously replaced by others who are equally inept. These amateurs swamp the more rational traders and inefficiencies are perpetuated with a continual turnover of naive speculators [Kaldor (1939)]. The bandwagon effect attributed to Baumol (1957) predicts that speculators buy and sell only after a price movement has started, which in turn accelerates price trends and causes
prices to deviate further from fundamental value. Other speculators may be affected by
the psychology of this artificial market and become more aggressive than other traders
because they are overconfident or overoptimistic. High leverage speculators who take
on higher risk and have higher returns are seen to perpetuate themselves as follows:

'When (inefficient) noise traders earn high average returns, many other investors
might imitate them, ignoring the fact that they took more risk and just got lucky.
Such imitation brings more money to follow noise trader strategies. Noise traders
themselves might become even more cocky, attributing their success to skill
rather than luck. As noise traders who do well become more aggressive, their
effect on demand increases.' (Shleifer and Summers, 1990, p.25).

Park (1993) extends and incorporates the above models by partly attributing the high
volatility around opening time and the decrease in volatility after opening, to speculative
behaviour of investors based on heterogeneous information that is created in nontrading
hours. Under Park's model, speculators are exposed to three risks: the volatility of the
normal price, risk due to errors of heterogeneous information, and the trading risk of
speculators. Park argues that the speculative price is more volatile than the normal price
subsequent to disclosure of public information and decreases posterior to the disclosure
of public information after the market opens. Park concludes that the heterogeneous
information created in nontrading hours increases volatility at opening and takes about 30-
45 minutes before the market reaches normal levels.

Froot, Scharfstein and Stein (1992) developed a combined information and speculative
model where traders have short-term investment horizons and tend to focus on one source
of information. Profit is earned on private information only if that information is
subsequently impounded into the price by the trades of similarly informed traders. The

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6 For example, Galbraith (1988) attributes the price bubble which preceded the 1929 stock market
crash to an irrational (almost manic) element, described as: 'the vested interest in euphoria [that]
leads men and women, individuals and institutions to believe that all will be better, that they are
meant to be richer and to dismiss as intellectually deficient what is in conflict with that conviction'
[Galbraith (1988, pp.xii-xiii)]. See also Garber (1990) and Shiller (1986) who offer similar
descriptions.
theory is driven by positive information spillovers: as more speculators study a given piece of information, more of that information disseminates into the market, and therefore, the profits from learning that information at an early stage are increased. Short-horizon speculation means that traders tend to focus (or herd) on single pieces of information, rather than on a diverse set of data which may include long-term fundamental information. In the short-term, speculators can only profit from information only if the information is publicly revealed or the next generation of speculators herd on that information. So the scramble is to become one of the first traders to gather and trade on private information released through private information traders and then to disseminate that information to the 'herd'.

Brown, Harlow and Tinic (1988) offered a rational explanation for the seemingly irrational overreaction in financial markets. They proposed an 'uncertain information hypothesis' that in the presence of imperfect information, rational risk-averse investors will respond by initially overreacting to bad news and underreacting to good news. This is caused by the sudden and dramatic arrival of information, which in turn induces short term volatility, temporarily increases risk levels and expected returns. Consequently, price changes in the immediate post event period after the arrival of positive information will reflect a series of positive returns. These post information price changes, whilst not rejecting market rationality, predict that financial markets react to uncertain information in an efficient, if not instantaneous fashion. This hypothesis is similar to the argument by Fama and French (1989) that expected returns to stocks and bonds vary throughout time in a manner which is consistent with fundamental business conditions. In other words there are time varying risk premiums.

In a similar vein, De Long, Shleifer, Summers and Waldmann (1990) proposed that speculators with erroneous (but stochastic beliefs) can earn higher rates of return compared to rational investors, because they are willing to bear a larger amount of risk. The participation of speculators in markets increases overall expected returns. This is because the more risk averse 'rational' investor requires a higher rate of return to
compensate for 'noise risk'. Noise risk is the risk that speculators may be irrationally pessimistic and push down prices in the near future. Given this additional noise risk, average prices will be below fundamental value in the short term. However, once the speculative noise is reduced, De Long, Shleifer, Summers and Waldmann predict that prices will mean revert back to fundamental value and give rise to the price reversal patterns predicted by the 'overreaction hypothesis'.

The above reviews of rational and irrational information theories are important to this thesis because a primary objective is to analyse how information is transferred into prices. Chapters four, five, six and eight apply a transfer function time series analysis to test for information transfer. The transfer function is modelled to incorporate three possible information transfer processes, specifically: the immediate impounding of information, the slow diffusion of information, and overreaction to information.

2.3.3 Information and Trading Volume

There are a number of reasons why trading volume is important to the study of financial markets and to the research undertaken in this thesis. Karpoff (1987) reviews the relation between price changes and trading volume and documents four reasons. First, the relation provides insights into the structure of financial markets and the rate of information flow and dissemination. Secondly, if price changes and volume are jointly determined the price changes can be interpreted as the market evaluation of new information, whilst the corresponding volume can be considered an indication of the extent to which investors disagree about the meaning of information. Thirdly, the price-volume relation may shed light on the distribution of speculative prices which appear leptokurtic over fixed trading intervals. Fourthly, price-volume relations may have significant implications for futures markets.

If transactions involving hedgers comprise only a small proportion of trading in futures markets then price variability may affect the volume of trading in futures contracts. If most trading in futures is speculative in nature, then interval-to-interval variations in
trading volume may be a proxy for interval-to-interval variations in speculative activity. Speculation may be a stabilising or destabilising factor on futures prices and may even spillover into the underlying asset market. Moreover, in futures markets information arrival may be maturity dependent as the contract time to expiration matures [Grammatikos and Saunders (1986), Samuelson (1976)]. For example, a given type of information might have little value one hundred days from contract maturity but as the contract approaches closer to maturity, the information might have greater impact. This is explained by the fact that as the contract nears maturity the probability of the value of that information being offset by the arrival of contradictory information is reduced. Thus while the rate of flow of information may be random over the life of the contract, the impact of information may be maturity dependent. Further, if there is a contemporaneous relation between trading volume and volatility then this would translate into higher trading volumes.

The study of the price-volume relation may provide further insight into the microstructure of financial markets. Following the seminal work of Clark (1973) a number of theoretical models have sought to explain the functional impact of trading volume on speculative markets. Clark assumed that returns follow a subordinated stochastic process in which the directing process is the cumulative volume, and that volumes in non-overlapping periods are independently distributed. Epps and Epps (1976) postulated that the volatility of the price change was dependent on trading volume and Tauchen and Pitts (1983) derived a mixing variable model whereby price changes and trading volume were simultaneously determined - the mixture of distributions hypothesis (MDH). The MDH states that the correlation between price volatility and trading volume should be positive because of a joint dependence on the amount of information impacting the market. For example, if the market is competitive, when unexpected information arrives, trading volume and prices should change contemporaneously as market participants revise expectations regarding the true (equilibrium) price. Grammatikos and Saunders (1986) contend that futures markets are information efficient and competitive, and consequently
when unexpected information arrives, trading volume and prices would change
contemporaneously.

Price variability and trading volume, however, may not be jointly determined in a
contemporaneous manner. In the sequential information model (SIC) there are
intermediate equilibrium prior to the final complete information equilibrium [Copeland
(1976), Morse (1981), Jennings, Starks and Fellingham (1981), Jennings and Barry
(1983)]. This implies that traders not yet informed cannot perfectly infer the presence of
informed trading. Consequently, the sequential arrival of new information to the market
generates both trading volume and price movements, with both increasing during periods
characterised by numerous information shocks. Using a similar argument, Fabozzi, Ma
and Lindsley (1988) apply an 'overshooting hypothesis' to combine the overreaction
arguments of DeBondt and Thaler (1987) with trading volume. They suggested that
security prices adjust to new information instantaneously whilst trading volume follows
with a lag. Eventually, the quiescent trading volume induced by portfolio revisions as a
reaction to revised prices, will reverse the price pattern which created the short term price
overreaction.

Epps (1975) has also constructed a model that implies that volume on price upticks is
greater than volume on downticks [see also Campbell and Hentschel (1992)]. His model
relies on behavioural distinctions between two types of investors: 'bulls' and 'bears'.
Bulls are more optimistic about the value of the security at the end of the trading period
and they react only to positive information. Conversely, the pessimistic bears react only
to negative information. In such a market the transaction demand curve consists of bull
traders, and bear traders comprise the supply curve. Epps demonstrates that the demand
curve is steeper than the supply curve and therefore the ratio of trading volume to a
positive price change is greater.

The study of the price-volume relation may also be important for investors and traders in
the market. Such well known adages as: 'it takes volume to make prices move' and,
'volume is heavy in bull markets and light in bear markets', reflect the perceived
importance of the relationship. Further, price and volume data are generally easily accessible and publicly available. For technical analysts who favour the psychological approach, the relationship may be used to extract the current 'mood' of the market. For fundamental analysts, if there is an economic relation between demand and supply, there may be lead-lag relationships which can be used to predict future movements. In either case, a better understanding of the statistical relation between price and volume may contribute to better market timing.

One aspect of the literature on trading volume is that there is no generally agreed consensus on how it impacts upon prices. Moreover, the importance of the volume of trading in futures markets has been the focus of substantial recent attention in the US, including studies by the New York Stock Exchange, the Commodity Futures Trading Commission, the Securities and Exchange Commission, the United States General Accounting Office and a Presidential Task Force. In Australia, the Australian Securities Commission released a report on over-the-counter derivative trading in May 1994. One focus of these reports has been the impact of derivative trading volume on price setting in futures and cash markets and proposals to restrict futures trading.

In chapter five the relationship between trading volume and SPI and AOI price changes is examined. This is an important question as it addresses the problem of how much of the price change can be attributed to information arrival or market structure, rather than simply to trading activity. Further questions about whether trading volume leads price changes or vice versa are also addressed.

Another strand of research has analysed the effects of price setting mechanisms, trading procedures, and the microstructure of the market on the evolution of prices and trading volume over the trading day. The following sections explain and outline the potential impact of the trading environment on prices and volume.
2.4 THE TRADING ENVIRONMENT

2.4.1 Price Setting Mechanisms

There are a number of mechanisms for setting prices in financial markets. Most modern stock exchanges set opening prices with a periodic clearing (or batch) transaction, where buy and sell orders accumulate during some pre-trading time interval and are then executed simultaneously at a single price which equates the quantity demanded to the quantity supplied. Thereafter, prices are primarily determined in a continuous market, where investors trade with market makers or are matched at quoted bid and ask prices. This section outlines a number of stock market price setting mechanisms and analyses the theoretical effects of each. The classification schema applied is the one used by Pagano and Roell (1991b) and consists of a batch auction, a continuous auction and a dealership market.

Batch Auctions

In a batch auction participants submit buy and sell orders up to a pre-specified time when they are accumulated and ordered. Prices are then determined by an auctioneer who defines a clearing price, constructed from the derived demand and supply schedules, at which all trades are executed. The auctioneer is typically a specialist rather than a mandatory disinterested auctioneer and, in some circumstances, the process is altered by allowing scope for the revision of orders in the event of an order imbalance. The revision of orders is allowed through a process by which tentative market clearing prices are called out to participants, who then rebalance their orders accordingly. Batch clearing markets are more usually employed at the opening of the market (New York, Milan, Tokyo), but are sometimes employed at resumption after lunch (Tokyo) or even at times throughout the trading day (Milan).
**Continuous Auction**

Under a continuous auction system traders submit orders to a centralised system that displays the best limit orders and executes all incoming market orders against these limit orders. Prices can be determined at any time when a public buy order crosses or matches a public sell order and in the words of Pagano and Roell (1991b, p.3), there is 'public limit order exposure'. Further, as trades are executed, the transaction price and quantity are recorded and made available so that all participants can trace the recent history of the order flow. The continuous auction system can be implemented via a computerised central trading system that displays all current information on screen, a manual order book, or else by pit or floor trading. In a pit or floor trading system trading information is facilitated by ticker tape reporting or by actually being present on a centralised trading floor. Examples of continuous auction markets are found on the Paris and Singapore stock exchanges.

**Dealership Markets**

In a dealership market continuous trading is augmented by the presence of dealers or market makers who provide additional liquidity to the market. In a market maker dealer system, designated dealers display bid and ask prices at which they are willing or obliged to buy or sell, and their impact on the market differs with regard to regulatory requirements. For example, dealers may be required to maintain price continuity or price stability, or they may simply be required to post quotes for prospective traders. They may also operate in competition for trades with each other, or be granted a monopoly. Quotations may be recorded in a manual or electronic order book with prices set by matching all orders immediately against the quotes. Alternatively, continuous trading may also take place in a trading ring or a pit, where prices are usually determined by direct negotiation between traders on the floor with the details being subsequently reported and published.

Under the dealership system all dealing is undertaken through the dealer and orders from members of the public do not cross directly. A characteristic of this system is that,
because each order is satisfied separately, the dealer may not be aware of the size, price or direction of orders executed by other dealers until they are reported. Exchange authorities dictate the speed at which publication should take place and this ranges from a few minutes up to 24 hours [see Pagano and Roell (1991b)]. A classic example of the market maker dealership system is the New York stock exchange.

Auctions and Dealers

Whilst there are individual variations within each of the trading structure groups, it is useful to classify the trading structures into dealership and auction markets to analyse inherent differences between the two market mechanisms [Pagano and Roell (1992), Amihud and Mendelson (1987, 1991a, 1991b)]. Speculators in an auction market can be viewed as playing a similar economic role as market makers in a dealership market, in that both absorb temporary imbalances in demand and supply, in order to extract a profit. For this reason, it could be easy to dismiss any mechanistic differences between the two markets as purely cosmetic. However, the specific role of the market maker in the dealership market means that they are different from speculators because they will often have both implicit and explicit obligations as well as privileges. A specific example is the requirement by some exchanges that market makers should set a 'tight market' (a small bid-ask spread), and provide liquidity. This can lead to market makers not maximising profits in the short run in return for long run rewards from the exchange itself. Another example is the requirement for market makers to quote firm prices which must be honoured if accepted by the market. This procedure effectively reveals the market makers trading strategy to all participants. The offsetting advantage given to the market maker is that they are not subject to competition for these quotes and are able to extract 'rents' from the market for providing information and liquidity.

A more explicit role sometimes allocated to the market maker is the obligation to offset any posted quote. This effectively provides insurance to traders by virtually eliminating execution risk and can be contrasted to an auction market where traders run the risk of obtaining an unfavourable price on a trade if an offsetting trade is not present. A trader in
an auction market can attempt to insure against execution risk by placing a limit order, but because there is no guarantee that the trade will take place, execution risk is reduced but not eliminated. Pagano and Roell (1992) demonstrated that the role of the market maker is socially efficient (in the sense that it is cheaper than the customer insuring themselves) when the dealer is less risk averse than the customers.

The Australian stock market is a client order driven continuous market. During normal trading hours, bids and offers are first matched on price and then by time priority. During the opening phase, from 1000 to 1009, bids and offers are matched on exact price and quantity or on a process of averaging using prices and trading volume. Once one price is determined, then a further price is calculated and so on up until the priority bid or offer price is satisfied [see Appendix 2.1 for a full description]. The process is therefore an auction system in which bids and offers can be modified in the pre-opening phase (0730 to 1000) but not in the opening phase. Further, prices are averaged and determined sequentially - not batched together and determined by one market clearing price. The Australian system is distinguished from other opening price setting mechanisms and provides the opportunity to compare the price behaviour at opening with previous overseas research.

2.4.2 Immediacy and Market Depth

A dealership market is inherently continuous whilst an auction market is discrete. An auction market can range from a single discrete clearing auction through to running a series of auctions. Obviously, as auctions become more frequent, traders have to wait less time before enacting a trade. This in turn benefits insiders who have access to superior information and reduces execution risk for traders who trade for liquidity purposes, because it shortens the time available for new information to be incorporated into prices. Conversely, as auctions become more frequent there will be greater operating costs because each transaction will have fewer trades, and the market will be thinner.
Pagano and Roell (1990) demonstrated the impact of these costs through a model that captured the effect of a market moving towards greater continuity. As frequency increased the number of participants (speculators, information traders and liquidity traders) decreased. As the number of speculators and liquidity traders fell, price variability increased and the risk-bearing capacity of the market decreased. Additionally, as the number of speculators decreased, each speculator had a greater impact on the market, which in turn induced them to act as imperfect competitors and to restrain their activity. Finally, informed traders benefited in this model because they were able to gain greater returns if there were fewer liquidity traders in each trade.

In summary, continuous trading provides immediacy for traders but decreases the depth of the market and lever the potential impact that speculators will have in the market place. In addition, if liquidity traders have some discretion as to when they trade the model can be extended to provide a result consistent with Admati and Pfleiderer (1988) who hypothesised that traders will concentrate their trades at certain times of the day in order to provide greater market depth and to partly overcome the costs of thin trading.

The Australian stock and futures markets employ a continuous trading mechanism, and in combination with the observation that trading volume is relatively thin, has a number of implications: (i) that the depth of the market is likely to be further reduced; (ii) that speculators will have a greater impact; and (iii) that liquidity and information traders will have limited opportunities to concentrate their trades. This further implies that Australian markets may be more speculative in nature but that information or volatility bunching will be less persistent or more concentrated.

2.4.3 Transparency and Visibility

Another area that is interesting from a theoretical standpoint is the effect that different trading systems may have on transparency. Transparency is the extent to which trading information is made publicly available after each trade or event. Complete transparency is defined as the dissemination in real time of the latest trades as well as quotations and
trading volume. Auction markets and market maker systems differ in the inherent price formation process as well as the degree to which the current order flow is visible to the competing market participants involved in price setting. Pagano and Roell (1992) demonstrated that transparency enhanced market liquidity and reduced transaction costs by reducing uncertainty. An auction price setting system allows market participants to observe the total net demand conveyed to the market and this is particularly the case for a continuous auction where demand and supply are constantly being equated. On the other hand, in a dealer market the market maker can only observe the current order flow as it is transacted between the dealer and traders. There is no public order crossing and in some cases the market maker must determine the market. Therefore, dealer markets are less transparent than auction markets. Moreover, the dealer has an incentive to increase trading spreads in order to cover increased uncertainty and losses to informed traders. However, one possible offsetting factor is that dealers, as insiders, may be able to induce or observe information and liquidity from 'information traders'. If this is the case then dealers may be able to learn from the information traders and pass on better 'deals' to their uninformed clients and reduce the returns to information traders.

Computer technology has played a major role in enhancing transparency by the use of screen trading. The ASE has recently transferred to a fully computerised system (SEATS) operated through the relative calm of the broker's office. A feature of this system is its information transparency and visibility. A range of information is displayed, including identity, outstanding bids and offers, trading volumes and past history. Further, once a price is determined then it is immediately observed. On the other hand, the Australian futures market utilises a pit trading mechanism to set prices whereby all bids and offers must be made by open outcry within the pit or trading area by a designated futures trader. No trading can be enacted outside the pit and trading cannot be prearranged. Once the trading chit recording details of the trade is completed a copy is given to a SFE computer operator so that the trade can be recorded. In turn the computer system relays information to price screens on the trading floor and to brokers offices. Moreover, there is a duty not to disclose any information about orders which individual
futures traders hold except only to the extent necessary to enable orders to be executed [SFE, TE 6.5 (1993)].

The hectic pit trading in the SFE compared with the relatively transparent and visible ASE suggests that futures markets in Australia are likely to be more volatile. Further, if the observations of Amihud and Mendelson (1991b) that the role of specialists in a dealership market reduces volatility and is a more effective value discovery process than continuous trading, then the Australian stock market may be more volatile and speculative compared to overseas stock markets.

2.5 OTHER MICROSTRUCTURE ISSUES

2.5.1 Trading Hours

Research has addressed structural issues such as the effect that trading halts, additional trading hours, evening trading sessions, and international cross listings have on prices and volume. For example, trading halts have been hypothesised to affect price volatility in security markets. This feature has especially received attention since the 1987 stock market crash which has concentrated attention on the volatility of security prices, especially futures markets, which have been blamed for inducing 'spillover volatility' into cash markets. A remedy often cited is to implement circuit breakers that halt trading when markets become excessively volatile. Greenwald and Stein (1991) contend that circuit breakers have a calming influence on market participants and a number of stock and futures exchanges have instituted mechanisms to implement market wide trading halts. A 250 point decline in the Dow Jones Industrial Average halts trading on the New York Stock Exchange for an hour. In contrast, it is also suggested that circuit breakers increase the uncertainty regarding the ability to exit the market and that an environment with trading halts may be less stable than an environment without halts [Gerety and Mulherin (1992)].
Financial markets experience a natural circuit breaker between the close of trading on one day and the opening of trading on the subsequent morning. If we also recognise that there is heterogeneous ability to bear overnight risk amongst traders and an absence of 24-hour markets, then closure may induce above average price movements and volume at the open and close of trading sessions. One would therefore expect that by adding trading hours from, say, an evening trading session, would dampen price and volume reactions at the regular daytime opening and closing of markets. For example, one might expect that the implementation of after hours trading would lessen the upturn in prices and volume at the end of the regular futures trading session and at reopening. Hansell (1989, p. 187) proposes that some short term traders may use ‘after hours trading capability for defensive reasons - to get out of something at night if the market is moving.’ The implication is that the after hours market allows day traders to hold greater positions without sacrificing immediacy, implying less relative activity at opening and closing. The effect of after hours trading has been illustrated in an analysis of the evening trading session of the CBOT’s Treasury bond futures contract by Ma, Peterson, and Kao (1990). They researched the effect of the addition of an evening session, in April 1987, on the trading patterns in the regular daily session. Among other things, the results indicate that ‘the last daytime hour shows a marked decline in volume relative to volume in the rest of the day after evening trading commenced’ [Ma, Peterson, and Kao (1990), p. 12].

Another form of market closure that has attracted some research interest is the Tokyo Stock Exchange which closes for lunch and has an additional morning close and afternoon opening. Amihud and Mendelson (1990) found that the morning opening was a period of relatively high volatility, but that the afternoon opening was no more volatile than the morning or afternoon closing. These results suggest that there is a lesser incidence of trades that transfer ‘closed-market’ risk between the morning close and afternoon open, vis-a-vis the number of such trades between the afternoon close and the morning open.
A comparison of the stock and futures markets in Australia provides the opportunity to analyse the trading time hypothesis and the market closure hypothesis.

2.5.2 Infrequent Trading

A further structural feature that may affect the dissemination of information is the degree of infrequent trading or the thinness of the stock market. The greater the nontrading of stocks in the stock index, the more the index represents an average of stale historical prices (usually detected by positive autocorrelation in price changes), rather than current prices. Infrequent trading has two major forms. The first form is when stocks trade during each defined interval but not necessarily at the close of each interval. This form has been detailed by Scholes and Williams (1977) and Miller, Muthuswamy and Whaley (1994) and is a particular problem when examining arbitrage price relationships between stock and futures or options and their underlying stocks [Brace and Hodgson (1991)]. The other form of infrequent trading is when stocks do not trade in every consecutive interval [Lo and MacKinlay (1990), Stoll and Whaley (1990b)].

Nonsynchronous trading and nontrading can be distinguished by the interval over which price changes or returns are computed. When returns are measured over longer periods (e.g. a month) then virtually all stocks will have traded at least once, but not all stocks will have traded contemporaneously at the close of the trading period. In other words trading will be nonsynchronous. When returns are measured over shorter periods (such as 15-minutes), then it is highly unlikely that all stocks in a price index will have traded at least once in each consecutive 15-minute period, and this is the nontrading effect. Therefore, as the trading interval compacts, the nonsynchronous trading effect effectively becomes the same as nontrading.

The importance of this microstructural factor to the thesis is that it may induce differences in the reaction times of cash indices and futures prices to new information. In turn this
may cause the cash index to react more slowly or be less volatile than it would be if it reflected current information. Miller, Muthuswamy and Whaley (1994) give an example to illustrate this point from the stock market collapse on Monday, October 19, 1987 when there were heavy imbalances in overnight orders. The futures market opened that day down seven percent, but the reported stock index did not fall immediately because it was based on the last transaction price of each component stock. This meant that the stock index mainly reflected the obsolete information contained in the prices of Friday's close, not the prices actually achievable at Monday's opening. As each stock traded the reported index level moved closer to the futures price, with the stock index taking about ninety minutes to revert to an equilibrium value.

Previous research has established the existence of thin trading by examining the autoregressive structure of the index. If all stocks do not trade instantaneously then there will be a lag in returns as trading takes place during later periods based upon information released in previous periods. In this thesis the impact of thin trading on the stock market is examined by applying time series analysis and controlling for this factor in subsequent statistical tests.

### 2.5.3 Bid-Ask Bounce

Possible contamination of prices may also arise from the random bouncing of transaction prices between bid and ask levels. Roll (1984) first showed that, even though price changes were serially independent, bid-ask price bounce induced negative first order autocorrelation in price changes. Stoll and Whalley (1990a) determined that for stock indices the trading of some stocks at bid prices was offset by other stocks which traded at ask levels - the bid-ask bounce was effectively diversified out. In contrast, the SPI futures contract is a single traded security. The bid-ask bounce cannot be averaged out and negative first order autocorrelation in price changes is likely to hold for short intervals, especially when the price movement attributable to new information is small relative to the size of the bid-ask spread.
This means that there is a possibility of bid-ask bounce in the futures market in the form of negative first order autocorrelation. Similar to the stock market this trading feature must be identified and filtered out before any subsequent statistical tests are undertaken.

2.6 SUMMARY

The purpose of this chapter was to establish a number of theoretical and potential impacts on prices and trading volume in the Australian stock and futures markets. The primary impact in Australia is likely to be public information which has accrued overnight from trading on overseas financial markets. The US stock market has the greatest potential impact.

One of the primary research problems that this thesis concerns itself with is the process by which information is impounded into prices. A number of information theories were examined and these theories form the analytical base for the mathematical and statistical analysis examined in later chapters. Briefly, models which assume instantaneous impounding of information into prices, a slow diffusion transfer and information overreaction are specified.

In a complex market setting the arrival of information, whilst the primary impact on prices and volume is information, the determination of prices and trading volume is complicated by a number of other secondary considerations. For example, the structure and range of different information traders, the degree of speculation, the opening price setting mechanism, the structure of the market and the impact of arbitrage and information feedback between the stock and futures market. These microstructural effects are complex and may be substantial. Figure 2.1 represents the potential effects of information and microstructures on the individual AOI and SPI markets. In later chapters these effects are taken into account when proposing research problems and designing statistical tests.
Figure 2.1 Schema representing potential impacts on prices and trading volume in Australian stock and futures markets.
Appendix 2.1: Opening Price Setting Mechanism on the ASE
[source Aitken, Brown and Walter (1994)) and Section 3.2 of the SEATS trading reference manual]

Special priority trading rules are applied to the opening of the Australian Stock Exchange (ASX). The normal continuous auction procedure is suspended and prices are set by matching prior bids and offers which is staggered as follows:

<table>
<thead>
<tr>
<th>Time</th>
<th>First Letter of ASE Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>A-C</td>
</tr>
<tr>
<td>1003</td>
<td>D-K</td>
</tr>
<tr>
<td>1006</td>
<td>L-Q</td>
</tr>
<tr>
<td>1009</td>
<td>R-Z</td>
</tr>
</tbody>
</table>

Opening times are randomly allocated to securities by the SEATS to a second within the range of plus or minus thirty seconds. The example below, which is based on Section 3.2 of the SEATS trading reference manual, shows how the opening price in each stock is determined. Assume that the following bid and offer quotes, in descending time and price priority, were posted prior to opening:

<table>
<thead>
<tr>
<th>Broker</th>
<th>BID Quantity</th>
<th>Price</th>
<th>Broker</th>
<th>OFFER Quantity</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>111</td>
<td>400</td>
<td>423</td>
<td>777</td>
<td>6,000</td>
<td>420</td>
</tr>
<tr>
<td>222</td>
<td>2,000</td>
<td>422</td>
<td>888</td>
<td>800</td>
<td>421</td>
</tr>
<tr>
<td>333</td>
<td>10,000</td>
<td>422</td>
<td>900</td>
<td>8,000</td>
<td>422</td>
</tr>
<tr>
<td>444</td>
<td>5,000</td>
<td>422</td>
<td>950</td>
<td>1,000</td>
<td>423</td>
</tr>
<tr>
<td>555</td>
<td>5,000</td>
<td>420</td>
<td>999</td>
<td>600</td>
<td>424</td>
</tr>
<tr>
<td>666</td>
<td>500</td>
<td>419</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

At the opening of the market overlapping bids and offers are matched in the following steps:
1) Match the best bid against the best offer at an averaged price, to the nearest tenth of a cent, to the extent that the stock is available.
2) Repeat step one until there is no overlap.
3) Open the market to normal trading.

The following example shows how the existing bids and offers are matched, the determination of the opening price, and how prices evolve in the first twelve minutes.

<table>
<thead>
<tr>
<th>Squinch</th>
<th>Bid</th>
<th>Offer</th>
<th>Quantity</th>
<th>Average Price Calculation</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>111</td>
<td>777</td>
<td>400</td>
<td>400 x 423 + 6,000 x 420</td>
<td>420.2</td>
</tr>
<tr>
<td>2</td>
<td>222</td>
<td>777</td>
<td>2,000</td>
<td>2,000 x 422 + 5,600 x 420</td>
<td>420.5</td>
</tr>
<tr>
<td>3</td>
<td>333</td>
<td>777</td>
<td>3,600</td>
<td>10,000 x 422 + 3,600 x 420</td>
<td>421.5</td>
</tr>
<tr>
<td>4</td>
<td>333</td>
<td>888</td>
<td>800</td>
<td>13,600</td>
<td>421.9</td>
</tr>
<tr>
<td>5</td>
<td>333</td>
<td>900</td>
<td>5,600</td>
<td>Equal Limits</td>
<td>422.0</td>
</tr>
<tr>
<td>6</td>
<td>444</td>
<td>900</td>
<td>2,400</td>
<td>Equal Limits</td>
<td>422.0</td>
</tr>
</tbody>
</table>

The opening price of the market is recorded as 420.2 and the market opens for continuous trading with the following prices posted.

<table>
<thead>
<tr>
<th>Broker</th>
<th>BID Quantity</th>
<th>Price</th>
<th>Broker</th>
<th>OFFER Quantity</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>444</td>
<td>2600</td>
<td>422</td>
<td>950</td>
<td>1000</td>
<td>423</td>
</tr>
<tr>
<td>555</td>
<td>5000</td>
<td>420</td>
<td>999</td>
<td>600</td>
<td>424</td>
</tr>
<tr>
<td>666</td>
<td>500</td>
<td>419</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER THREE

LITERATURE REVIEW: EMPIRICAL RESEARCH

3.1 INTRODUCTION

This chapter reviews the empirical literature relating to a study of price movements, trading volume and arbitrage pricing in index futures and related stock markets. The purpose of the review is to assist in defining the empirical context of this thesis and to provide a background for the research undertaken. The relationship between stock and futures markets encompasses information impacts (both public and private), feedback between the two markets and the effects of various microstructures. The relationship is wide ranging and complex (see Figure 2.1). Consequently, the purpose of the chapter is not to provide an exhaustive review but to outline the seminal research and the results of extensions to security markets other than in the United States. Further research, when relevant, is reviewed and added into individual chapters.

One important feature of the previous empirical studies is that it has been mostly undertaken in large thinly traded security markets in the United States and Japan. In the case of Australia, which is a small thinly traded market, there has only been limited research in futures markets and to date this has been mostly confined to an analysis of interday data. This means that there is limited published empirical research in Australia which analyses the effects of microstructures and trading mechanisms on intraday futures prices. A second observation is that the research literature is relatively recent with almost all of the research conducted within the last eight years.
Sections 2 and 3 of this chapter are concerned with micro patterns in stock and futures price returns and volatility. Prior to 1985, very little empirical research was possible in this area owing to the difficulty associated with obtaining the necessary data. The recent research has been made possible by the availability of 'quote capture' and 'tick-by-tick' data sets, the increased power of computers and the deregulation of markets. The review includes an analysis of trading and nontrading effects and intraday patterns. Section 4 reviews patterns in trading volume and the empirical relationship between trading volume and price innovations. Section 5 of the chapter examines the literature on intermarket feedback. This encompasses two strands - the proposition that futures markets provide a medium to efficiently transfer information to the cash market and effectively play a price leadership role (the stabilising hypothesis), or that speculators in the futures markets cause high volatility which spills over into the underlying stock market (the destabilising hypothesis). The final component of this chapter summarises previous research involving questions of arbitrage and deviations from the theoretical cost of carry model.

As previously mentioned stock index futures contracts were chosen because of the spectacular growth in financial futures on the SFE, the potentially important economic benefits they offer and the politically sensitive profile they carry.¹ A comparison of the intraday price evolution in both stock and futures markets is useful in that it allows some control over the different microstructure effects in these two related, but separate markets. This is important because price evolution over the day may depend upon different attributes such as: trading mechanisms and structures, heterogeneous trading clientele, or different information flows over the trading period. The possibility of arbitrage trading between these markets offers several further complicating factors.

¹ Trading in index futures has been attributed as a major contributing factor to the October 1987 stockmarket crash [Brady (1988)] and recent reports have recommended regulation of derivative trading [USGAO (1994), ASC (1994)].
3.2 MICRO PATTERNS

3.2.1 Trading and Nontrading Prices
Trading time prices behave differently to nontrading time prices. French (1980), in a study of the Standard and Poor's (S&P) 500 stock index, first established the existence of a negative average Monday return of -0.1681% over the period 1953 to 1977. The French study was extended and confirmed by Gibbons and Hess (1981) and Lakonishok and Smidt (1988). Rogalski (1984) refined this research by examining the issue of how much the negative Monday return (Friday close to Monday close) could be attributed to the nontrading period over the weekend (Friday close to Monday opening) and how much could be attributed to trading itself (Monday opening to Monday close). He found that when daily returns were decomposed into trading and nontrading periods, a nontrading negative 'weekend effect' dominated. The S&P Friday close to Monday close return of -0.1167% decomposed into a nontrading return of -0.1315% and a Monday trading return of +0.0148%.

Cornell (1985) was one of the first researchers to compare the weekend effects in the S&P 500 stock index and index futures markets and to suggest that the prices in these two markets did not always react in a similar fashion. Cornell used data from the period May 1982 to July 1984 and found that the Friday's close to Monday's open return was significantly negative in the cash market, but there was no weekend effect in the futures market. He suggested that the Monday effect existed because of the peculiar behaviour of cash prices during nontrading hours. These results were confirmed by Finnerty and Park (1988) who used a different data set by comparing stock and futures prices from the Major Market Index (MMI) over the period July 1984 to July 1986. Further, using 15-minute observations, Finnerty and Park determined that the negative return in stock prices started to take place from around 1330 on Friday and was reversed by a positive Monday return. They suggested that the nontrading weekend phenomena was related to

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2 Chiang and Tapley (1983) previously found day of the week effects in a data set of twenty one futures commodities, but the set did not include any stock index futures contracts.
institutional factors which were unique to the stock market. Other observations were a higher relative opening price volatility in cash markets (which was consistent across all days), higher relative volatility in futures during the interior and a lunch hour nontrading effect with minimal price movements.

The comparative trading and nontrading return analysis was expanded by Maberly, Spahr and Herbst (1989) who extended the Cornell data set (from 1983 through 1986) and used a number of different stock and futures indices. They observed a negative weekend nontrading return for stock and futures index returns with the stock market having a much greater negative return. For the remainder of the week the nontrading return was positive for both stock and futures indexes. The trading period returns also differed between stock and futures markets. For the Value Line Index (VLI) returns were positive for Mondays and Thursdays, for both stock and futures indexes, but on Tuesdays, Wednesdays and Fridays, VLI futures had negative returns whilst the stock index had positive returns. Similarly, the S&P stock index trading period returns were usually positive and opposite in sign to the S&P futures trading returns. Maberly, Spahr and Herbst suggested that the negative nontrading weekend returns were consistent with negative macro information being released over the weekend and the negative Friday returns on futures markets were an anticipation of the weekend effect.

Trading prices have also shown to be significantly more volatile than nontrading prices. This was first demonstrated by French and Roll (1986) who reported that equity returns on the New York and American Stock Exchanges were more volatile during trading hours when compared to nontrading hours. Returns during trading hours were 13.2 times more volatile than returns for mid-week holiday nontrading returns; 71.8 times more volatile than weekend returns; and 99.6 times more volatile than holiday weekend returns. French and Roll estimated that approximately 4% to 12% of the daily return variance was caused by speculative activity and that most of the remaining variance was caused by private information released through the process of trading. The above research induced a number of further empirical research articles which explored the
microstructure of intraday trading and the nature of intraday information flows, market microstructure and the effects of trading mechanisms on trading prices.

3.2.2 Intraday Trading Prices in Stock Markets

It has also been documented that there are distinct patterns in intraday trading time prices. One of the first studies on the evolution of intraday prices was a study by Wood, McInish and Ord (1985) who used 15-minute returns for stocks listed on the New York Stock Exchange (NYSE) for the six months period ending February 1972 and all of 1982 trading year. Mean returns and return variances were shown to have a U-shaped structure during the day. McInish and Wood (1991) extended the 1985 study by analysing first-order autocorrelations of interday 24-hour returns terminating at 15-minute time intervals during the trading day by using 1400 NYSE stocks for calendar year 1984. They observed a U-shaped intraday pattern in autocorrelations and found that the serial correlation of a portfolio of thinly traded securities was positive and higher than a similar index constructed from liquid and well traded securities.

A larger data set was used by Harris (1986) who examined 15-minute returns for all common stocks traded on the NYSE for the period December 1981 through January 1983. He found that for the first 45 minutes of trading, mean returns were negative on Monday (-0.13%) whilst on other weekdays, returns were positive (0.09%, 0.14%, 0.12%, and 0.10%). Returns at the end of the day were all positive and, in general, mean intraday returns at the beginning and end of the trading day were five to ten times larger (in absolute value) than returns which accrued in the middle of the day. F-tests confirmed, at the 5% level, that Monday returns were different from the rest of the week and the first three 15-minute intervals were different from the next twenty one 15-minute intervals. Equivalence of the intraday mean returns was accepted only for the inner twenty (10.45 - 15.45) 15-minute returns. There were also some other general patterns noted - a rise in price between 1230 and 1330 and a fall between 1430 and 1515. Harris hypothesised that size differences may have implications for information theories. He
found a slower price reaction on Mondays for smaller firms and suggested that they do not adjust quickly to macroeconomic information. Harris also suggested that the long adjustment time (45-minutes) to new information at the opening of trading, may be a consequence of regulations which require market specialists to maintain an orderly market.

The possibility that the higher price activity at opening (and later) could be attributed to the effects of market microstructures was examined by Amihud and Mendelson (1987, 1989, 1990, 1991a, 1991b) and Amihud, Mendelson and Murgia (1990). This research reviewed the impact of price setting mechanisms on 24-hour opening, closing and intraday price returns on the Stock Exchanges of New York, Tokyo and Milan. The Amihud and Mendelson (1987) study compared the time series behaviour of stock returns for the period February 1982 to February 1983 using open-to-open and close-to-close returns for thirty stocks listed on the New York Stock Exchange (NYSE). They found that the variance of the open-to-open returns was higher than the close-to-close return variance for 29 out of the 30 stocks (the average ratio was 1.20), and the autocorrelations of the open-to-open returns were predominantly more negative than those of the corresponding close-to-close returns. They concluded that this was evidence consistent with more noise and with a mean reversion pattern at the opening of trading. Moreover, the difference between the opening and closing volatility was greater when the first transaction of the day was executed in a continuous trading mechanism. They argued in an overview article [Amihud and Mendelson (1991b)] that the clearing transaction (and the role of specialists in the process) reduced volatility and was a more effective value discovery process than continuous trading, but that part of the unusual activity at opening was associated with the arrival of overnight information. This research was later confirmed by Stoll and Whaley (1990) who extended the research to all NYSE stocks.

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3 The mechanisms compared were the continuous dealership market, whereby investors trade with market makers at their quoted bid and ask prices, and the other was the periodic (call) clearing procedure.

4 The use of a 24-hour window methodology controls for any information impact. If the different trading mechanisms have no effect on stock prices, the variances and autocorrelations should be the same.
The intraday analysis was extended into the Japanese share market by Kato, Ziemba and Schwartz (1989) who examined transaction data over the period 1974 to 1987. Negative returns were found for Monday and Tuesday but, unlike the US results, the negative returns continued throughout the day until the last hour of trading. For the remaining days of the week, returns for the first hour of trading were positive with returns for the last hour of the trading day consistently positive for all days. Kato, Ziemba and Schwartz argued that the high late afternoon Wednesday returns were consistent with settlement procedures at the end of this day, and the other patterns were due to international market influences adjusted for time zone effects between New York and Tokyo.

The Tokyo Stock Exchange Price Index (TOPIX) also provided an opportunity for Chang, Fukuda, Rhee and Takano (1993) to examine the impact of mid-day trading closures and possible market 'moods' on intraday prices. They used minute-by-minute prices over the period August 1987 to April 1991 which they decomposed into two daily trading sessions and into 'bull' and 'bear' periods. Chang, Fukuda, Rhee and Takano observed a number of patterns which were related to trading structures and market expectations. Returns were significantly negative at morning close and afternoon reopening after lunch, with these results robust between bull and bear markets. In the bear market period there was a negative overnight return, with positive overnight returns in the bull market period. Further, the volatility pattern showed two distinct U-shaped curves during the morning and afternoon trading periods. The volatility at the opening of the morning session was the highest of the trading day and the volatilities at afternoon opening and closing were roughly equal. The morning trading period volatility was 140 times greater and the afternoon trading period volatility was 60 times greater, than the volatility of the overnight nontrading period. Finally, correlations between adjacent minute-by-minute returns were higher at the beginning and close of a trading session with the magnitude greater during the bear market with negative return correlations more

5 TOPIX has two daily trading sessions - a morning session from 900 to 1100 and an afternoon session from 1300 to 1500.
frequent during bull market periods. This research showed that market closures had an impact on prices and suggested that prices may be a function of the constituent trading clientele.

There has also been some limited unpublished research on intraday price movements in Australian stock markets. Overall they indicate that whilst there are a number of similarities with the larger well traded markets, Australian markets might also have idiosyncratic patterns influenced by the arrival of overnight information and thin trading. There is more relative action at the opening of the market in Australia. Intraday volatility in Australia is L-shaped and returns in the first hour are negative after a positive overnight return. Hathaway (1990) analysed the minute-by-minute price and volume behaviour of the 100 largest firms listed on the Australian Stock Exchanges over the period October 1988 to May 1990. Hathaway observed larger bid-ask spreads in the first hour of trading (1.10%) compared to the remainder of the day (constant at 0.75%). The larger bid-ask spreads were not explained by increased trading volume, which accumulated at a steady rate during the day, but were attributed to a temporary risk premium caused by the uncertainty of the price effects of overnight information from world markets. Hathaway also reported positive returns during the morning session and negative returns in the afternoon trading session.

Aitken, Brown and Walter (1994) documented all regular trades on SEATS from September 1990 to September 1992. They found a uniform and strong positive rate of return for the last transaction of the day (0.05%); an average positive return of 0.02% for the first minute but an overall negative first hour return; and a positive last hour return with the most prominent spike during the second last minute (0.0215%). Volatility (absolute rate of return) in the first hour was 200%-300% times higher and in the last hour about 50% higher, than volatility during the middle of the day. Compared to the US studies volatility had a less pronounced U-shaped pattern. Trading volume built up during the first hour of trading, declined during the middle of the trading session and increased towards the close. There was also lower average trading volumes on Monday.
The time frame of the analysis was extended to a long term period of five years and the impact of trading structures was examined by Brailsford (1994) who used 5-minute data on the AOI from April 1989 to December 1993. Brailsford decomposed the analysis into two sub-periods; before and after the introduction of screen trading and the establishment of a lagged price setting mechanism to determine opening prices. For the full data set there was a large positive overnight return, negative returns in the first hour and between 1400 and 1500, and a large positive closing return. Volatility, measured by standard deviation and absolute returns, was generally L-shaped. Further, the change in trading procedures led to a spreading of returns and volatility at the opening of trading, but returns and volatility were unchanged across the remainder of the trading day. Brailsford also suggested that there was an association between futures market trading and stock market volatility.

3.2.3 Intraday Trading Prices in Futures Markets

The research on intraday patterns in stock markets has been extended and compared to the patterns in stock futures markets. This comparison has been useful because, theoretically in an efficient market, both stock and stock futures markets should react similarly to the same information set. If this is not the case, then the different trading clientele or microstructures in futures markets may provide an explanation. There have been a number of differences (and similarities) in the evolution of intraday prices in these two markets.

The Finnerty and Park (1988) study of 15-minute MMI stock and futures prices from July 1984 to July 1986 found a number of intraday patterns. Returns in both markets were generally positive at opening and during the first hour of trading, there was a lunchtime effect when returns diminished, and positive returns at the close of trading. Finnerty and Park determined the volatility of stock prices in the first hour of trading to be abnormally high compared to other trading hours but in the futures market volatility was not as pronounced at opening. Both markets, however, showed a general U-shaped intraday pattern in volatility which was slightly lower at the close compared to opening.
This general U-shaped pattern has also been confirmed by an analysis of conditional volatilities. Cheung and Ng (1990) used a GARCH (1,1) model to examine the 15-minute return dynamics of the S&P 500 index and index futures data for the period April 1982 to June 1987. They first reported that the unconditional volatility of futures price returns was higher than the cash index volatility, except for the first 30-45 minutes of trading when cash volatilities were higher than the volatility of futures prices. Second, conditional futures volatilities were relatively higher early and late in the day, with volatility at its lowest between 1200 and 1215. Third, the conditional volatility of the cash index dropped dramatically during the first 45 minutes of trading and then remained at a stable level. Chan, Chan and Karolyi (1991) also calculated conditional 5-minute volatilities using a bivariate AR(1) - GARCH (1,3) model from 5-minute 'quote capture' prices for the S&P stock and futures index over the period August 1984 through December 1989. They observed U-shaped pattern and established that the intraday volatility patterns in both the cash and futures market demonstrated strong persistence and predictability. They also observed fat tails and sharp peaks in both cash and futures returns, negative skewness which was more pronounced in futures, positive autocorrelation in the cash market up to two lags and negative autocorrelation in the futures.

More recent research has jointly reported trading volumes, the incidence of price reversals, discussed the importance of information arrival and different trading procedures on intraday prices. Ekman's (1992) study is an example of a comprehensive descriptive analysis. Ekman used 'time and sales' data to calculate 15-minute returns from the S&P 500 index futures market over the period January 1983 to November 1988. Ekman did not compare his results to a stock market control sample but found that the intraday pattern in S&P futures returns was roughly similar to that observed by Harris (1986) in the stock market. There was a negative Monday morning weekend return, positive returns over the Monday trading day, a negative Friday close with the negative weekend effect beginning to emerge from about 1200 noon on Friday. The absolute value of returns (as a proxy for volatility) showed a U-shaped pattern, with significantly
higher volatility in the first hour of trading. A further observation which was different from Harris (1986), but similar to Finnerty and Park (1988), was a decline in volatility during the last half hour of trading. Ekman argued that this effect may be partially attributed to a change in information arrival due to the close of the NYSE 15 minutes before the close of the futures market. Ekman also recorded a U-shaped pattern in trading volume with a slight downturn at the close of trade. Price reversals were also examined and observed to follow an S-shaped pattern with reversals greatest in the morning and on Fridays. A final observation was that trading periods had a higher volatility than nontrading periods, with the weekend average volatility much lower than would be expected if volatility was caused solely by the constant arrival of public information.

An analysis of the impact of microstructures and the intraday evolution of stock and futures prices under a different market structure was undertaken by Yadav and Pope (1992). They examined intraweek and intraday seasonalities in cash and futures risk premia using hourly data from the UK FTSE 100 index, a market which has different settlement procedures and trading microstructure compared to the US. They found that the UK stock market did not efficiently incorporate into prices the entire interest costs inherent in its settlement procedures. There were positive returns in the first hour of trading, cash prices increased when the market was open and futures prices increased when the market was closed. Further, they found a systematic fall in returns between 1400 and 1500 with significant negative returns from 1430 to 1500. One explanation put forward was that these returns coincided with the opening of the US market and 'the UK market tends to be too 'bullish' about the US market and needs a correction when the US opening market price is actually observed' [Yadav and Pope (1992, p.259)].

The only comparative study of intraday stock and futures prices in Australia has been undertaken by Hodgson, Kendig and Tahir (1993) who applied a short term data set. They applied 15-minute data for the period January 1992 to September 1992 to describe trading time returns (excluding overnight returns) on the AOI and SPI. Hodgson,
Kendig and Tahir reported large negative returns for both markets at 1015 and 1430, but a divergence between AOI and SPI returns at 1600. The AOI return was large and positive and the SPI return was negative. Volatility had a L-shaped pattern in contrast to the U-shaped pattern in the US and Japanese markets and was comparably higher in the first hour of trading for both markets. Finally, volatility was consistently higher in the SPI futures market compared to the AOI.

3.2.4 Autocorrelations

The autocorrelation of stock and futures returns differs between markets and over time. Research on the intraday autocorrelation prices in stock futures markets has concentrated on comparing them to autocorrelations in the related stock market. The motivation for this empirical research was to test the proposition of relative inefficiency/efficiency of futures markets compared to stock markets. For example, if there are 'frictions', such as transaction costs and nonsynchronous trading in smaller thinly traded stocks, cash index prices will be slow to adjust to new information and this can induce spurious first-order autocorrelation in these returns. Conversely, changes in index futures prices should have lower autocorrelation because they have a comparative advantage in transaction and liquidity costs [Silber (1984), Berkowitz, Logue and Noser (1988)]. Given these a priori arguments stock price index changes would be expected to have a positive autocorrelation and autocorrelation in futures price changes should be around zero. A further consideration was that the futures contract had a finite life. This structural difference means that the autocorrelation structure of futures may be related to contract time to expiry or to trading volume induced by imminent contract closure.

The intraday comparison of stock and futures autocorrelations was first undertaken by MacKinlay and Ramaswamy (1988). They examined and compared the autocorrelations of 15-minute returns in the S&P stock market and futures index over the period September 1983 to June 1987. The first order autocorrelations were high and significantly positive for the stock index and small and insignificantly negative for the
futures series. MacKinlay and Ramaswamy argued that this result suggested that forces other than stale prices in the cash index were causing these autocorrelations.

The results of MacKinlay and Ramaswamy (1988) were confirmed by Cheung and Ng (1990) and Chan, Chan and Karolyi (1991) who used longer and more concentrated data sets. Cheung and Ng (1990) found that the first order autocorrelation of 15-minute futures returns was statistically insignificant and the first order autocorrelation of returns in the stock index series was positive and ranged from 0.038 to 0.409 across the sixteen contracts. Using a longer and more detailed price return series Chan, Chan and Karolyi (1991) analysed the S&P 500 stock and futures autocorrelation coefficients for 5-minute return intervals up to the sixth lag to a data set spanning August 1984 to December 1989.

For the cash stock index, statistically significant positive autocorrelations were discovered for the first and second lags with negative autocorrelations after 15 minutes. Futures returns displayed negative autocorrelations at 10 and 15 minute lags. All authors interpreted this as evidence of the nonsynchronous trading problem that persisted in cash stock indices.

The analysis of the intraday behaviour of futures autocorrelations was extended by Martell and Trevino (1990) who studied price behaviour over the life of the contract. They found that the intraday serial correlation gradually changed from small but significantly positive at the beginning of the life of the contract, through to strongly negative as the contract approached maturity. An explanation given was that when markets are relatively inactive, large orders to buy or sell are broken into smaller orders and executed one at a time (with the hope of obtaining a better price). This activity results in prices being driven gradually up (with orders to buy) and gradually down (with orders to sell). Martell and Trevino also found that a strong relationship existed between intraday price behaviour and the trading activity of the market. Intraday serial correlation moved from significantly positive in inactive days to very strong and negative in the more active days and, as trading volume increased, the incidence of price reversals also increased. They hypothesised that liquid and active markets reduced the risk to a floor
trader by lowering the time traders were required to hold positions and this resulted in a smaller bid/ask price spread.

The autocorrelation of stock and futures price returns differs between geographical markets. This was observed by Lim (1992) who extended the research on to Japan by using a random sample of five days of all transactions data for each contract from June 1988 to September 1989 on the Nikkei futures and cash index. Lim found that neither the cash nor the futures index returns exhibited significant positive or negative autocorrelation. Unlike the MacKinlay and Ramaswamy (1988) results for the S&P 500 index, the Nikkei index did not feature stale prices, and the evidence did not support the hypothesis that futures prices were more volatile than cash prices. Ho, Fang and Woo (1992) further internationalised the research to the Hong Kong futures market by analysing 'tick by tick' transactions data from the Hang Seng futures and cash markets for seventeen days from April 1991 to July 1991. They reported that the autocorrelations for both the cash and futures returns were weak and inconsistent, and neither the cash nor the futures price appeared to be consistently more volatile.

In Australia the autocorrelation structure is stronger and positive in the stock market. This was established by Twite (1991) who examined the autocorrelation of daily closing price data from the AOI and SPI over the period February 1983 to December 1988. A statistically significant positive first order autocorrelation of 0.14 was found for AOI returns. In contrast, futures returns did not exhibit any significant first order autocorrelation. Twite attributed these results to thin trading in the underlying shares of the cash sharemarket index, caused by the nontrading in the smaller component shares.

### 3.3 PRICE CHANGES AND TRADING VOLUME

As previously outlined in chapter two there are a number of reasons why trading volume is important to the study of financial markets and to the research undertaken in this thesis. Briefly they are as follows: (i) an analysis of trading volume might provide insights into
the structure of financial markets and the rate of information flow and dissemination; (ii) if price changes and volume are jointly determined the price changes can be interpreted as the market evaluation of new information, whilst the corresponding volume can be considered an indication of the extent to which investors disagree about the meaning of information; (iii) the price-volume relation may shed light on the distribution of speculative prices which appear leptokurtic over fixed trading intervals; and (iv) price-volume relations may have significant implications for futures markets. [Karpoff (1987)]. There are a number of empirical research papers that provide evidence on the relationship between trading volume and returns. A selection, which includes a number of research papers in futures, is reviewed below.

3.3.1 Stock Markets and Trading Volume

A number of research papers provide indirect evidence on the relationship between trading volume and stock returns and volatility. Returns and volatility tend to follow a U-shaped pattern during the day [Harris (1986), McInish and Wood (1985, 1990a), Yadav and Pope (1992), Chang, Fukuda, Rhee and Takano (1993)]. Trading volume also exhibits a U-shaped pattern over the trading day [Jain and Joh (1988), Wei (1992), Wood, McInish, and Ord (1985)] which in combination suggests a positive relationship between returns, volatility and trading volume. Harris (1987) provided more direct evidence by finding a positive correlation between trading volume and changes in squared returns for individual NYSE stocks.

The study by Jain and Joh (1988) used hourly price and volume data from the S&P index over the years 1979 to 1983 and established intraday patterns and correlations between volume and prices. Applying F-tests derived from analysis of variance regressions they determined that average returns and trading volume were significantly different across hours of the day. Returns were positive in the first hour (except Monday) and the last hour of trading and negative in mid afternoon. Trading volume was highest in the first

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6 In applying the F-tests they ignored data dependencies which could distort the statistical results.
hour (50% higher than the average over the day), declined monotonically until the fourth hour and then increased in the fifth and sixth hour. This U-shaped intraday volume pattern was robust across days of the week and between bull and bear markets. Trading volume was also found to be lowest on Monday, increased during midweek and declined on Thursday and Friday. Jain and Joh observed a positive correlation between trading volume and absolute returns which was stronger in the first and last hours and weaker in the middle of the day. They interpreted this as being consistent with the hypothesis by Clark (1973) that when there is no information available trading is slow and price processes evolve slowly, and when information arrives trading is brisk and price processes evolve much faster.

The mixture of distributions hypothesis [Epps and Epps (1976)] linking price changes, trading volume and the rate of flow of information has been empirically tested by Lamoureux and Lastrapes (1990). They assumed that the daily returns and trading volume were drawn from a mixture of distributions as the amount and rate of information arrival varied. The mixing variable was the arrival of information and trading volume was assumed to be a proxy for the mixing variable. Lamoureux and Lastrapes incorporated trading volume in the conditional variance equation of a GARCH (1,1) model. They examined 20 US stocks and found that the inclusion of the transaction volumes in the variance equation removed the significance of the $\alpha_1$ and $\beta_1$ coefficients and greatly reduced the persistence of volatility. This result implies that the inclusion of trading volume as a mixing variable provides an alternative for the GARCH process.

The Tokyo Stock Exchange (TSE) opened for half a normal trading day on three Saturdays a month during the period January 1973 through January 1989. This trading feature provided the opportunity for Barclay, Litzenberger and Warner (1990) to examine the impact of extended trading hours and public information releases on trading volume and price volatility. They observed the following: (i) Trading volume was lowest on Mondays and highest on Wednesdays and Fridays; (ii) Weekly volume was 21% higher
when there was Saturday trading compared to non-Saturday trading; (iii) The weekend variance was twice as large when there was Saturday trading and this was followed by reduced daily variance in the subsequent days which resulted in the weekly variance being the same; and (iv) The cross listing of US stocks on the TSE or Saturday trading in Japan does not affect the pattern of return variances of those stocks in the domestic market. Barclay, Litzenberger and Warner concluded that the higher weekend variance was not caused by traders overreaction to each other's trades (the noise hypothesis), or by public information releases (Japanese companies do not release information on the weekend). They argued that the change in the pattern of daily variances when Saturday trading occurs was caused by the shifting of informed and discretionary liquidity trading in response to an increase in the volume of liquidity trading on Saturdays. The increased weekend variance was therefore a reflection of the additional private information released through trading and the reduced variance on subsequent days reflected a reduction of the amount of information revealed through informed trades. These results were considered to be consistent with the rational trading models of Kyle (1985) and Admati and Pfleiderer (1988) where private information revealed through trading causes price volatility.

Gerety and Mulherin (1992) argued that investors may differ in their willingness to hold positions overnight and this may explain the U-shaped pattern in volatility and trading volume. Day traders are characterised by their unwillingness to assume the risk of adverse news that may occur overnight and on weekends. They predicted that the greater the expected overnight volatility the heavier will be volume at the close, and that trading volume in the opening hour would be influenced by the previous night's volatility. Gerety and Mulherin collected hourly data from the NYSE Dow Jones Composite Index for the period 1933 through 1988. They found a U-shaped pattern in trading volume which was stronger earlier in the data set. They cited this as evidence to weaken the argument that institutional investors were driving increased trading volume at the close, because performance was assessed on close to close returns. Consistent with the predictions of their model, trading volume at the close was related to expected overnight
price volatility and volume at the opening to the previous night's volatility. They concluded that trading halts caused investors to overreact and leave the market more quickly.

Foster and Viswanathan (1993) hypothesised that the interday and intraday differences in trading volume may be a function of size and information flow. They examined the trading volume for sixty firms traded on the NYSE in 1988 ranked by firm size deciles. They found that Monday trading volume was only significantly lower for actively traded firms. This was consistent with discretionary liquidity traders being more likely to alter their trades when there was a strong public information signal and avoiding days when there was a lot of private information. Consistent with other research there was a concentration of trading volume in the first half hour of trading and intraday trading volume was positively associated with volatility. Additionally, the interday variations in trading volume and the association with volatility were weaker compared to the intraday variations. Finally, they found that there was a positive relation between adverse selection trading costs and trading volume. They concluded that the Admati and Pfleiderer (1988) and Foster and Viswanathan (1993) models could not, in their current forms, explain the fact that trading volume was highest when trading costs were high for the intraday tests. They suggested that it may result from the market maker's monopolistic power, greater inventory costs during this active period, or intraday variation in public and private information which makes the middle portion of the day fundamentally different from the open or close.

In Australia there has been very little research which has specifically examined trading volume. Brailsford's (1994) unpublished study on daily trading volumes in the AOI over the period April 1989 to December 1993 represents one of the few to date. Using three proxies for trading volume (transactions, number of shares, and dollar value), Brailsford observed that trading volume was lower on Mondays and generally increased over the week. Further, there was an asymmetrical relationship between trading volume and price changes (positive price changes had a more significant relationship with trading volume),
and there was a reduction in the persistence of variance when trading volume was added to the variance equation of a GARCH (1,1) model which supported the observations of Lamoureux and Lastrapes (1990) in the US.

### 3.3.2 Futures and Trading Volume

Futures trading volume has a strong U-shaped pattern [Lauterbach and Monroe (1989), Bessembinder and Sequin (1993)] and a contemporaneous relationship between unexpected trading volume and price changes [Bessembinder and Sequin (1992)]. In contrast with the results from the stock market trading volume is not a surrogate for volatility persistence [Locke and Sayers (1993)].

There are two important seminal research studies which established the contemporaneous relationship between futures trading volume and prices. Grammatikos and Saunders (1986) used daily observations for five different foreign currency futures markets to obtain evidence on the relation between price variability and volume of trading. During the research period, from March 1978 to March 1983, they found a strong contemporaneous correlation between trading activity (volume and open interest) and price volatility consistent with the mixture of distributions hypothesis. Further, using a Granger-Sims causality test, they found that in 10 futures contracts volume caused volatility and in 16 futures contracts volatility caused volume. The remaining 84 contracts exhibited bidirectional causality and they concluded that in futures markets price volatility and trading volume were contemporaneously correlated. Rutledge (1986) proposed that day-to-day variations in futures trading volume were a surrogate for day-to-day variations in speculation. He then argued that if statistical causality ran from trading volume to price volatility, then it may be cited as support for speculators increasing volatility with support for price limits and regulation of futures markets. Evidence in the other direction (volume following volatility) may be construed as support for the relaxation of futures regulations. Using Granger-Sims causality tests and daily data, Rutledge examined 15 futures commodities in the US for three random time periods of approximately four months. Rutledge found that in the 33 cases in which causality
was identified, only two showed causality from trading volume to price variability and concluded that trading volume responded to price variability rather than causing it.

Bessembinder and Seguin (1992) extended the examination of the price-volume studies cross-sectionally by using daily data from the S&P 500 stock and futures market. They noted that active futures markets were empirically associated with decreased rather than increased stock market volatility. They found a positive relation between cash volatility and the contemporaneous trading volumes in both futures and spot, with a much stronger relationship with surprises in trading volume. However, futures trading volume and open trading interest had a dampening effect on stock volatility when the level of futures activity was high. They concluded that futures trading improved liquidity and depth in stock markets, did not provide a conduit for destabilising speculation and stock volatility was reduced with the resulting deeper markets.

The volume-volatility relationship also depends on the class of traders involved and the direction of increases or decreases in trading volume. Bessembinder and Sequin (1993) argued that reductions in futures open trading interest were a proxy for futures speculators (or day traders) who were not prepared to hold open positions overnight. On the other hand, increases in open interest were seen as a proxy for the amount of hedging activity or the willingness of futures traders to risk capital. They used daily settlement prices and trading volume over the period May 1982 to March 1990 for eight futures contracts spread across currency, financial commodity and metal futures contracts to test their hypothesis. The results were as follows;

(i) there was a strong positive relation between contemporaneous volume and volatility,
(ii) the impact of unexpected volume changes was between two and thirteen times greater than the impact of changes in expected volume,
(iii) the effect of unexpected volume shocks on contemporaneous volatility was asymmetric - positive shocks were associated with 76% greater volatility,
(iv) trading volume that resulted in changes in open interest appeared to have a larger impact on prices than trades that left open interest unaltered,
(v) volatility was negatively related to the expected level of open interest, and
(vi) there was less evidence of significant correlations between signed returns and trading volume.

Locke and Sayers (1993) used one-minute returns from the S & P 500 Index futures contract during April 1990 to examine the role of contract trading volume, floor transactions, the number of price changes, and executed order unbalance as proxy variables for information flows in reducing variance persistence. They found that trading volume and the number of price changes per minute were equally successful information arrival proxies. In contrast to the results of Lamoureux and Lastrapes (1990) they found significant variance persistence after controlling for trading volume. They suggested that price changes may be attributed to market information signals, as distinct from the usual information arrival proxies (such as volume). For example, favourable public announcements could cause a relatively large increase in price changes without a similar increase in trading volume and trading, per se, did not fully explain persistence in returns volatility.

3.4 INTERMARKET FEEDBACK

3.4.1 Intermarket Information Transfer and Price Discovery

A theoretical model developed by Cox (1976) proposes that in the presence of an active futures market, a cash market is more efficient in the sense of having faster price adjustments because futures markets have lower transaction costs. If futures markets are transactionally more efficient than cash markets then they are expected to adjust more rapidly to new information. Thereafter, through either the process of observing information traders in the futures market, or via the actions of program trading and/or arbitrage, the information is transferred to cash market prices. It is argued that if the link between the cash and futures market is severed, the lag of stock market prices behind the futures market will increase, and thus the improvement in information transfer would be lessened. Intermarket information transfer or price discovery between futures and cash
prices could be one explanation as to why cash and futures prices diverge over the course of the trading day.

Garbade and Silber (1983) were among the first researchers to formally model the relationship between spot and futures prices. Using data on physical commodities they determined that futures markets dominated cash markets, with approximately 75% of new information affecting the futures price first. The intraday information discovery question in stock index futures markets was addressed by Kawaller, Koch and Koch (1987). They used minute by minute data on the S&P 500 futures and cash index from January 1984 to December 1985 to calculate cross correlations and used three stage least squares estimation. Kawaller, Koch and Koch found that futures prices consistently led cash price movements by 20 to 45 minutes with cash stock prices rarely leading futures by more than one minute.

The results of Kawaller, Koch and Koch were supported by Stoll and Whaley (1990a) who used five minute interval transaction data for both the S&P 500 and the MMI\(^7\) stock and futures index to investigate information transfer and price discovery. Another perspective to the problem was attained by adjusting the returns series for nonsynchronous trading, and comparing this 'true' series to that of an individual stock. They concluded that futures prices contained predictive power for cash prices for up to ten minutes but in general, the movements were contemporaneous.

In contrast to other researchers who concluded that price leadership was efficient information transfer, Finnerty and Park (1987) cited their research as evidence to support press and SEC claims that the use of stock index futures (especially by program traders) was fuelling volatile price swings in the spot equity market. Finnerty and Park regressed the change in the cash price against the lagged change in the futures price for the MMI and the Maxi Major Market Index (MMMI) over the period August 1984 through August 1986. They found that a majority of both contracts showed a significant relation between

\(^7\) The MMI is a price weighted index composed of 20 of the most actively traded stocks on the NYSE. The use of this index controls for nonsynchronous trading found in indexes with thinly traded stocks.
a change in the futures price and the subsequent change in the spot index. The dependencies were spread over time to expiration for MMMI but for the MMI the relationship increased as time to expiration diminished. Finnerty and Park concluded that their results supported the notion that the 'tail was wagging the dog'. This study, however, has been questioned on grounds of data problems and deducing causality [see Gordon, Moriarty and Tosini (1987) and Herbst and Maberly (1987)].

Cheung and Ng (1990) applied an improved statistical methodology. They used a GARCH (1,1) model to filter out the deterministic component of returns and the Granger, Robins and Engel (1986) test for causality in the variance and found that futures and cash price volatility moved in unison. For price changes there was evidence that futures prices led cash prices for at least 15 minutes and up to 30 minutes. Overall, there was a strong instantaneous correlation in price changes ranging from 0.58 to 0.71. Cheung and Ng concluded that new information was impounded into prices with greater speed in the futures market than the stock market because speculators or investors with private information were more likely to transact in the futures market because of lower transaction costs.

Chan, Chan and Karolyi (1991) made several contributions to the intraday lead-lag literature by analysing the variance as a measure of information transfer, controlling for the nonsynchronous problem (the lead-lag relationship may be induced by this factor), and applying a more sophisticated statistical technique. They used 5-minute 'quote capture' information on the S&P index and index futures from the Chicago Mercantile Exchange for the period August 1984 through December 1989. To overcome the nonsynchronous trading problem the tests were replicated with 5-minute data from the MMI price weighted index of 20 of the largest and most actively traded NYSE stocks together with 5-minute returns for IBM stock. They based their research on the proposition that the volatility of an asset's price, and not the asset's simple price change, was directly related to the rate of flow of information to that market [Clark (1973), Tauchen and Pitts (1983), Ross (1989)]. Using a bivariate AR(1) - GARCH (1,3)
process the conditional volatility in each of the two markets was found to be affected by events in its own market as well as the other market. The lead-lag relationship between intraday volatilities was not the same as that uncovered in the lead-lag relation between returns in previous research - that futures led cash returns. The past volatility of cash (futures) was found to be an important predictor of the future volatility of futures (cash) prices. Further, the lead-lag relationship between price changes appeared to diminish over the period, whilst the intermarket dependence of volatility was unidirectional and grew stronger. The results were robust to controlling for the potential effects of infrequent trading of the component stocks in the index and other market frictions. The results of this research have questioned the previous findings that new information disseminates in the futures market first and then, subsequently in the cash market. In contrast there was evidence of a much stronger dependence in both directions in the volatility of price changes between the cash and futures markets than was observed in price changes alone. The information contained in price innovations that originate in the cash market is transmitted to the volatility of the futures market and information in price innovations that originate in the futures market is transmitted to the volatility of the cash market. They concluded that their evidence was consistent with the hypothesis that new market information disseminated in both the futures and stock markets and that both markets served an important information discovery role.

Herbst and Maberly (1992) noted that the Standard and Poors (S&P) futures market closed 15 minutes later than the NYSE which enabled the futures market to play a possible price discovery role. The higher volatility in futures markets at the end of the day was hypothesised to be associated with private information gathering. They argued that informed traders would gather private information during the course of the trading day, and that they would prefer to transact in the futures market rather than cash markets because: futures transactions were less costly, more liquid, and provided a relatively

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8 French and Roll (1986) found that stock returns tended to be more volatile during trading hours than nontrading hours, and concluded that private information was the principal explanatory factor behind high trading time variances. Ross (1989) demonstrated that in an arbitrage free economy, return volatility was directly related to information production - the variance of price changes was equal to the rate of information flow.
easy and cost effective means of establishing short positions. Informed traders will also trade on their information before the market closes - otherwise they face the possibility of information decay over the non trading period [Admati and Pleiderer (1988)]. Herbst and Maberly used 15-minute end of day futures return over the period May 1982 through March 1988 and found that the flow of information was a function of the day of the week. End of day information flow was found to be relatively large on Fridays and relatively small on Wednesdays. Additionally, positive and negative end of day futures returns were associated (p = 0.881) with positive and negative next day opening cash market returns, and the end of day futures return volatility was concluded to be related to information production during the next trading day.

A number of other studies assert that there is no unambiguous price discovery role played by the futures market. Schwarz and Laatsch (1991) found that neither the futures nor the cash market maintained price leadership. Schwarz and Laatsch used 1-minute, 5-minute, 15-minute, 30-minute and hourly data as well as daily and weekly observations to analyse the MMI Maxi future and cash market for the period September 1985 through March 1988. They declared that the lead/lag attributes of a market were dynamic and would fluctuate across periods and even within a day. Lim (1992) used 5-minute data from June 1988 to September 1989 from the Nikkei cash and futures and a first order autoregressive model to prewhiten the series before testing for significant cross correlations. There was no evidence to support a lead-lag relationship, with only the contemporaneous price changes of the futures and spot indexes significantly correlated. A similar result emerged from the work of Ho, Fang and Woo (1992) in their analysis of the Hang Seng index futures and spot index prices in Hong Kong. The cross correlations of the futures and spot index price changes displayed large, significant contemporaneous cross correlations. However, none of the lead-lag cross correlation coefficients were significant, indicating that neither index served a price discovery role.

In Australia, Hodgson, Kendig and Tahir (1993) tested for intraday price leadership or information transfer in Australian markets by calculating cross correlations for the returns
on the SPI and AOI. They found that futures led cash prices by up to 45 minutes, but during different periods, cash prices led futures prices by up to 30 minutes. They concluded that there was no stable futures/cash stock information transfer relationship in Australia. In contrast, Twite (1991) calculated cross correlations for end of day returns on the lagged SPI futures and AOI index. The results showed significant (at the 10% level) cross correlations for the futures price change and lagged cash price changes. Twite concluded that futures prices led cash prices and that this was a function of thin trading in the Australian stock market.

3.4.2 Intermarket Volatility Spillover

The above studies examined the proposition that futures markets provide a medium to efficiently transfer information to the cash market and effectively play a price leadership role. The earlier research suggested that the futures market led the stock market. However, later research is mixed and raises questions as to whether the futures market is, indeed, an efficient conduit for information. The research by Finnerty and Park (1987) and Chan, Chan and Karolyi (1991), in particular, raises important questions about the effect that trading in the futures index has on the volatility of the cash stock market. One view is that the higher volatility in futures markets, caused by more highly levered and speculative participants, may be a major contributing factor in increasing the volatility of the cash market [Cagan (1981), Brady (1988), Edwards (1988a, 1988b)] mainly through program trading and other arbitrage strategies.

This section reviews the background research on whether the introduction of futures and derivative trading increases the volatility in the underlying cash security. There are a number of papers on commodity futures and other financial futures examining the question of volatility spillover from futures to cash markets which predate the recent concerns related to stock index futures. In order to provide an historical background a selection of the earlier research on commodity and financial futures is now reviewed. This is then followed by a brief review on index futures volatility spillover.
Commodity Futures

Working (1960) used unadjusted t-tests to compare the intramonth and intraseason price variations in the spot prices of onions, before and after the introduction of futures trading. He found that there was no increase in the volatility of spot prices but found some reduction in both the intramonth and intraseason variances, especially when there was a substantial amount of hedging in onion futures. Gray (1963) and Johnson (1973) both updated and supported the findings of Working in onion futures.

Powers (1970) examined the effect of futures trading on weekly cash prices of pork bellies and live cattle for four years before and after the introduction of futures. He decomposed the cash price series into a systematic component which represented fundamental economic conditions, and a random component. Using an F test on the difference between the two variances he showed a significant reduction in the variance of the random component after the introduction of futures trading. He attributed this reduction to the increase in speed and the wide area of saturation with which futures markets disseminated information. Taylor and Leuthold (1974) further examined the effects of the introduction of futures trading in live cattle and found a significant reduction in the variability of weekly and monthly cash prices.

GNMA Certificates

Much of the previous empirical research on the possibility that destabilising speculation in financial futures markets will be transmitted to the cash market causing abnormal volatility, has been carried out in the US on Government National Mortgage Association (GNMA) securities.

Froewiss (1978) regressed the weekly percentage price change in spot GNMA prices on the weekly percentage price change in spot 10 year Treasury bond prices for 29 months before the introduction of GNMA futures and for a 26 month period after trading was introduced. Froewiss found that there was no significant difference in the slope regression coefficient in both periods. These results were interpreted to mean that futures
trading had not changed the relative variability of GNMA spot prices. Froewiss also examined the relationship between the GNMA spot price and the GNMA spot price lagged one and two weeks using a univariate time-series analysis. The results indicated no significant difference in the autoregressive coefficients before and after futures trading began. However, the standard error of those coefficients had fallen significantly. Froewiss concluded that systematic movements in GNMA spot prices had not changed but random movements had been reduced significantly. Finally, Froewiss regressed the percentage change in GNMA spot prices on the same variable lagged one week. The regression was significant before but not after futures trading began. This was interpreted by Froewiss to mean that new information affecting GNMA certificates was more rapidly absorbed into spot prices, as a result of the introduction of futures trading.

In summary, Froewiss concluded that there were no destabilising effects on spot markets as a result of futures trading; and that the introduction of futures trading may well have reduced random price variability thus resulting in more efficient information processing in spot markets.

Figlewski (1981) regressed the monthly variation of daily cash GNMA prices on the amount of open interest and volume of trading in GNMA futures markets. Figlewski's multiple regression model also used a set of control variables which included measures of volatility in related markets, breadth and liquidity of the spot GNMA market, and the level of cash prices in the GNMA market. The coefficient of the open interest variable was significant and positive, whilst the coefficient of the trading volume variable was not significant for 8% coupon certificates. For 9% certificates the trading volume variable was positive and significant but the open interest variable was not. Figlewski interpreted these results to mean that the trading of GNMA futures had increased the volatility of GNMA cash prices. This increased volatility was attributed to the actions of a class of investors in the GNMA futures markets who acted on imperfect information. Moriarity and Tosini (1985) retested Figlewski's (1981) data set from November 1975 to February 1979 and extended the time period of the study to June 1983. The results of their regression tests indicated that there was no evidence that the introduction of GNMA
futures trading had increased cash market volatility. Further, they suggested that Figlewski's results had been caused by data quality and the effects of collinearity between futures and cash market variables. This observation was also confirmed by the use of univariate ARIMA residual cross-correlation methods which found that there was no significant dependence between cash and futures volatilities and futures volume in either subperiod, but indicated a simultaneous association which was considered to be consistent with integrated cash and futures markets.

Regression analysis with dummy variables and a multivariate time series model with an intervention term, were used by Simpson and Ireland (1982) to test the spot price volatility of GNMA certificates before and after trading in futures. They regressed daily and weekly changes in yields and average yields of 8% ten year GNMA certificates against changes in the yield on ten year US. treasury bonds and 10 year GNMA securities. They found no change occurred in the spread between the volatility of the GNMA rate and the control variable rate, or their relative volatilities. A Chow test also indicated that neither the slope nor the intercept terms changed in the period after trading began in GNMA futures. The time series analysis showed that the standard errors of the models were low and the Box-Pierce Q statistic suggested that the series were reduced to white noise in all cases. Simpson and Ireland concluded that trading in GNMA futures did not increase the volatility of spot prices in GNMA certificates, either on a daily or weekly basis.

Finally, Bhattacharya, Ramjee and Ramjee (1986) attempted to determine the causal impact of the volatility in futures markets on the volatility in the cash markets for GNMA securities using ARIMA time series methods. Weekly estimates of volatility of 8% and 9% GNMA spot securities and GNMA futures for less than 3 months and 3-6 months were used for the period December 1979 to December 1982. They found weak evidence that futures market volatility caused cash spot market volatility for 8% securities in shorter time periods. But, the results for 9% securities in shorter time periods were not significant as were the results for both 8% and 9% over longer periods. Overall, the
authors concluded that speculators in GNMA futures were well informed and did not cause destabilising in cash markets.

*Share Price Index*

Edwards' (1988b) study which examined the long term effect of the introduction of index futures on the cash index market was the seminal piece of research in stock and stock futures markets. Edwards used F-tests to analyse the difference in variances on close to close prices between cash and futures before and after the introduction of the S&P 500 and Value Line Index (VLI) futures contracts. He first observed that futures prices were significantly more volatile than spot prices and then tested to determine if that volatility was transmitted to cash prices over the long term. Edwards found that the volatility of the S&P cash index was significantly higher before the start of futures trading and there was no significant change in the volatility of the VLI. Edwards concluded that the introduction of futures trading had no long term impact on the volatility of the underlying stock markets.

Brorsen (1991) hypothesised that if the increased use of computers and the introduction of futures and options markets increased the flow of information between related markets, this would result in a lowering of transaction costs in the cash market with a subsequent dampening of autocorrelations. Brorsen used the closing prices of the S&P 500 stock index from July 1962 through December 1986 to test this hypothesis. Using the Q-statistic of Ljung and Box (1978) he found highly significant autocorrelations at a number of lags before the introduction of futures trading, but after futures were introduced, only the first-order autocorrelation coefficient was significant. Brorsen also used an F-test to test for the differences in the variances of log changes of the S&P cash index over 1-day, 5-day and 20-day periods. The statistical evidence confirmed that the variance increased over time. Brorsen argued that reduced market frictions had increased market efficiency and this had led to an increase in the variance of short run price changes. Brorsen concluded that the speed of adjustment of the cash market to information had increased after the introduction of futures trading.
Other research in this area has concentrated on analysing the short term volatility effects when index futures, index options and options on futures expire simultaneously (the triple witching hour). Stoll and Whaley (1987) found that whilst there was no statistical difference in mean return the standard deviation of return on the spot S&P 500 was significantly greater during the last hour of trading on expiration days compared to other days. Further, stocks not included in the S&P 500 index did not display increased volatility, and part of this last hour movement was reversed on the day following expiration. Kling (1987) attributes this volatility to the weakness of the specialist trading system in the US. Regulatory advantages given to specialists allow them to drive other, potentially more efficient, traders out of the market thus reducing the overall supply of liquidity.

3.5 ARBITRAGE AND MISPRICING

It is well known that the availability of an underlying basket of stocks and a futures contract written on those stocks, provides an arbitrage link between cash and futures markets. One other research approach is to examine the arbitrage mispricing series between the stock index and the futures contract in order to provide evidence on the effectiveness of the arbitrage link between the two markets. In an efficient market there should be no evidence of sustained arbitrage mispricing or any structural dependence in the mispricing series - the path of the series should fluctuate randomly around zero. The empirical observations have contrasted sharply with theoretical expectations.

In a perfect frictionless market, arbitrage implies that the price of an index futures contract will be the spot price of the cash index plus the opportunity costs of holding the arbitrage portfolio. Cornell and French (1983) derived a cost of carry model which provides a theoretical futures price as follows:

\[
F(t, T) = S(t)e^{(r-d)(T-t)}
\]  

(3.1)

where;
$F(t, T)$ is the theoretical futures price at time $t$ for a contract expiring at time $T$ ($T>t$),

$S(t)$ is the price of the spot cash index at time $t$,

$r(T-t)$ is the non-stochastic risk free interest rate over time period $t$ to $T$, and

$d(T-t)$ is the non-stochastic and continuous dividend yield over time period $t$ to $T$.

Mispricings are calculated as the difference between the actual and theoretical futures prices and are often explained as the existence of arbitrage opportunities in the markets. Intraday studies of the mispricing series are important because they provide an indication of the strength of arbitrage activity between markets and whether the information or microstructure effects in each market have a significant counterveiling effect on the activities of arbitrageurs.

There have been a number of studies which document the mispricing series between cash index and futures markets using intraday closing price data [including Cornell and French (1983), Figlewski (1984), Merrick (1988) *in the US*, Bowers and Twite (1985) *in Australia*, Brenner, Subrahmanyam and Uno (1989) *in Japan*, and Yadav and Pope (1990) *in the UK*]. Most of this early research found frequent and prolonged deviations from theoretical values. One explanation put forward for these 'mispricings' was the immaturity of the arbitrage sector connecting the cash and futures markets. It was argued that a growing market takes some time to develop its arbitrage base sufficiently to eliminate arbitrage profits. To this end, Rubinstein (1987, p.84) stated that after a five period of market development: 'I am forced to the conclusion that even today the growth in index futures trading continues to outstrip the amounts of capital that are available for arbitrage.'

Yoo and Maddala (1991) suggested that there is a return premium for bearing risk in futures markets. They discussed two major functions a futures market could serve - a risk sharing role and a price discovery role. A price discovery role means that futures prices represent all the information about the future cash price so that economic agents can make plans and decisions by looking at the futures price. On the other hand, if
speculators in futures markets are risk averse as a whole then hedgers must pay a risk premium to speculators as compensation for the risk sharing in futures markets. If this is the case then the cost-of-carry futures price should normally be slightly below the future spot price to induce speculators to assume some risk. The difference between this future spot price and the expected futures spot price is a risk premium called 'normal backwardation', based on the assumption that hedgers, as a whole, are net short (ie. speculators continuously hold net long positions). Yoo and Maddala tested whether hedgers pay a risk premium to speculators by analysing six commodity futures for thirty contracts and five foreign exchange futures for twenty contracts during various periods from 1977 through 1988. They found for large hedgers average profit is significantly negative for most of the futures contracts and interpret this as evidence that large hedgers pay a risk premium. Also for large speculators, average profits were significantly positive and higher than large hedger's average losses. Yoo and Maddala's general conclusions were that large speculators have information which is superior to information of small traders, large speculators receive a risk premium from large hedgers but also make money in some markets (wheat, soybean and oil futures) from superior information.

Other explanations include stochastic interest rates, tax timing effects [Cornell and French (1983)], lumpy dividends, transaction costs [Modest (1984), Yadav and Pope (1991)], short selling constraints [Brenner, Subrahmanyam and Uno (1989)] and time to maturity [Merrick (1988), Yadav and Pope (1991)]. One other possible reason for the observed mispricings which is important to this thesis is that stock and futures markets do not have contemporaneous closing times. By matching intraday transactions a more exact measure of arbitrage activity can be undertaken, and a micro level analysis of the evolution of the mispricing series can be made. A review of this research is now undertaken.

### 3.5.1 Intraday Mispricing

One of the first studies on intraday mispricing was undertaken by MacKinlay and Ramaswamy (1988) who compared the theoretical S&P futures price with its actual value
using 15-minute intraday data. They reported that the theoretical price was violated 14.4% of the time even after accounting for reasonable transaction costs and that whilst the extreme mispricings of the early years had been eliminated, the markets maturation had not been sufficient to eliminate arbitrage opportunities. Large positive autocorrelations for all eight 15-minute lags in the mispricing series showed that mispricing tended to persist, a positive relation was found between the magnitude of the mispricing and the time to maturity, the mispricing series was path dependent, and the autocorrelation of the first difference in the mispricing series was negative.

Brennan and Schwartz (1990) utilised the mispricing series calculated by MacKinlay and Ramaswamy (1988) as the basis for further research on arbitrage opportunities. The mispricing series was assumed to follow a Brownian Bridge process and the parameters were estimated and found to be nonstationary over the sample contracts. From the time series pattern in the mispricing series, Brennan and Schwartz developed an optimal arbitrage strategy and tested its performance over the period June 1983 to June 1987. The average profit net of transactions costs was estimated to be positive, and between 0.54 and 1 S&P 500 index points.

Another mispricing data set was analysed by Chung (1991) who analysed the MMI spot and futures index from July 1984 to August 1986 for mispricing. The study used transactions data, performed both ex post and ex ante tests of arbitrage by assuming execution lags of 20 seconds, two minutes and five minutes. In addition the tests incorporated transaction costs and the uptick rule which only permits short selling when the previous price has increased. Ex post mispricings were found by Chung to have decreased over time and were approximately 5% of observations. When the tests were run with an execution lag even fewer profitable arbitrage actions were discovered. Chung concluded that arbitrage opportunities were not as prevalent as some previous studies (using end of day closing prices) had suggested and had decreased in intensity as the market matured. Further, by regressing the ex ante profits on ex post violations, the
mispricing signal was claimed to contain little value in predicting the true ex ante profit, with even a negative relationship occasionally existing between the two variables.

A number of studies in Asian markets have confirmed the US research. Lim (1992) tested for intraday arbitrage opportunities in the Nikkei futures and cash index for twenty random days of transaction data over the period June 1988 to September 1989. The documented mispricing error over these sample days was between -1.2% and 1.2%, with an average mispricing of -0.11%, and a large and positive first order autocorrelation in the mispricing series. The Hang Seng futures and spot indices (in Hong Kong) were investigated by Ho, Fang and Woo (1992), using intraday transaction data with a one minute interval with a 17 day sample taken randomly from the period April 1991 to August 1991. Estimates of transactions costs were separately calculated for exchange members, day traders, and overnight traders and considered in the analysis. For exchange members an average of 68.9%, for day traders 70.8%, and for overnight traders 72.4% of transactions, lay within efficient arbitrage bounds. In addition, the majority (approximately 90%) were overpriced and the mispricing series displayed high and persistent positive autocorrelation. They concluded that, 'once a contract is mispriced in one transaction it will be mispriced for several subsequent transactions.'

A market with significantly different settlement procedures and trading microstructure was researched Yadav and Pope (1992) who examined intraday seasonalities in futures mispricing using hourly data from the UK FTSE 100 index. Using F-tests and nonparametric Kruskal-Wallis and Mann-Whitney tests, mispricing returns were found to have an inverted U-shape over the trading day. They were significantly negative and different from the remainder of the day during the first and last trading hour intervals with the negative mispricing more pronounced on Friday afternoons. Yadav and Pope observed that there was a rise in cash prices during Friday afternoons but there was no corresponding rise in futures. They argued that this result was consistent with the conjecture that cash prices rose because market makers did not wish to hold short open positions over the weekend, whilst exchange members and locals on the London
International Financial Futures Exchange (LIFFE) tended not to hold large open overnight positions.

The Australian contribution to index futures arbitrage research is limited, and is mostly restricted to analysis using end of day data. The exception is the study by Hodgson, Kendig and Tahir (1993) who analysed 15-minute data on the AOI and SPI over the period January 1992 to September 1992. Using a transaction cost window of 0.5% they found that 33.6% of ex post arbitrage opportunities violated the transaction cost bounds. When an execution lag of 15-minutes was allowed in the stock market then 26% of the ex ante arbitrage opportunities still remained. Bowers and Twite (1985) used daily data from February 1983 to December 1984, and tested for violations of the cost of carry model. Although significant deviations were found, the study ignored transactions costs and taxes. Other explanations for the apparent arbitrage opportunities included thin trading and short selling frictions, but none of these explanations were consistent with the data [see Bowers and Twite (1985) and Hodgson, Kendig and Tahir (1993)]. Twite (1990) extended this analysis to incorporate transactions costs and taxes, and found that the arbitrage opportunities were more limited after including these variables. Johnson (1988) criticised Bowers and Twite for not testing actual trading strategies when determining the existence of arbitrage opportunities, ignoring execution impossibilities, and the fact that the markets would not immediately adjust to the theoretical futures price. Johnson repeated the Bowers and Twite (1985) tests and found that there was no evidence of substantial arbitrage profits and that the mispricing fell as the futures expiration date drew closer. Heaney (1992) modelled index futures to include tax effects, stochastic interest rates, dividends and general equilibrium effects. Heaney applied regression analysis to daily SPI data and found evidence of mispricing but the model did not provide descriptive power over actual index futures prices. Heaney's conclusions suggested that the mispricing was caused by unknown deficiencies in the model.
3.5.2 Arbitrage or a Statistical Illusion?

The negative autocorrelation in the first difference of the mispricing series observed in a number of the above studies indicates that there is a negative relationship between changes in mispricing and the level of mispricing in the previous period. This implies that when mispricing deviates from its mean value it is pulled back towards the mean. This 'mean reversion' process has been attributed to the action of arbitrageurs who trade the cost of carry relationship between cash and futures markets [MacKinlay and Ramaswamy (1988), Brennan and Schwartz (1990) and Yadav and Pope (1990)].

Miller, Muthuswamy and Whaley (1994), however, proposed an alternative explanation for the observed negative autocorrelation in basis changes - that it is merely a 'statistical illusion' arising because many stocks in the stock index portfolio trade infrequently. They argued that even if arbitrage never occurred, reported basis changes would appear to be negatively autocorrelated as lagged stocks eventually traded and got their prices updated. An example given to illustrate this point was the stock market collapse on Monday, October 19, 1987 when there were heavy imbalances in overnight orders. The futures market opened that day down seven percent, but the reported stock index did not fall immediately because it was based on the last transaction price of each component stock. This meant that the stock index mainly reflected the obsolete prices of Friday's close, not the prices actually achievable at Monday's opening. As each stock traded the reported index level moved closer to the futures price, with the index taking about 90 minutes to revert to equilibrium value.

Miller, Muthuswamy and Whaley (1994) used 15-minute observations from the basis between Standard and Poor's 500 (S&P) and Value Line Composite Index (VLCI) cash and futures markets for various periods from April 1982 through March 1991 to determine the extent to which the observed negative autocorrelation in the basis could be traced to the actions of index arbitrageurs. They first eliminated all pairs of consecutive price changes during the period 1988 to 1991 in which the theoretical mispricing exceeded 0.25%. Mispricings outside these transaction cost bands were taken as
potential arbitrage opportunities. After this filter was applied the autocorrelation dropped
only slightly from -0.416 to -0.360. The second test involved an examination of the first
order autocorrelation of 15-minute basis changes for the Value Line Composite Index
(VLCI). This index is one that cannot be arbitrated because it is geometrically weighted
and the possibility of replicating the underlying index is ruled out. The first order
autocorrelation of the VLCI basis changes was -0.182. They argued that this behaviour
could not be attributed to arbitrage activity. In order to gauge the prevalence of index
arbitrage, the trading volume of arbitrage activity was obtained from the NYSE superdot
system which records the simultaneous purchase or sale of at least 15 different stocks
with a market value of $1 million or more. They found that index arbitrage accounted for
about 43% of program trading which is a very small (3.8%) percentage of total trading
volume. Finally, Miller, Muthuswamy and Whaley purged the effects of thin trading
from the S&P 500 stock index and examined the impact on the first order autocorrelation
of the basis. After adjustment, the first order autocorrelation fell from -0.369 to -0.252.
Taken together the evidence implied that formal arbitrage accounted for only a small
fraction of daily trading volume and could not fully explain the negative autocorrelation in
basis changes. Miller, Muthuswamy and Whaley concluded that the differences in the
frequency of trading of individual stocks within stock indexes induced the mean reversion
behaviour in the basis.

The contentions of Miller, Muthuswamy and Whaley (1994) have generated some debate
in the literature about the cause of mean reversion in index mispricing. Yadav and Pope
(1993a) statistically analysed and compared the mean reversion properties of the index
futures mispricing series by applying the Dickey-Fuller unit root test. They used the 15-
minute mispricing series data set calculated by MacKinlay and Ramaswamy (1988) on the
S&P 500 index over the period September 1983 to June 1987, to compare with hourly
mispricings derived from the FTSE 100 index over the period April 1986 to March 1990.
The mean reversion parameter was statistically significant but not very strong. On
average it was 0.018 in the US and higher at 0.038 in the UK. Mean reversion had a U-
shaped pattern over the course of the trading day. It was significantly lower on
Mondays, and was higher with decreasing futures contract time to expiration and high levels of mispricing in the previous period.

Yadav and Pope countered the argument of Miller, Muthuswamy and Whalley (1994), that mean reversion was a statistical illusion generated by infrequent trading in index stocks, by running simulations. They concluded that the simulations could generate negative serial correlation in the mispricing series but could not generate mean reversion when defined as the negative dependence of the change in mispricing on the level of mispricing in the previous period. They also argued that empirically observed seasonalities in the mean reversion parameter were opposite to those predicted by explanations based on infrequent trading. For example, mean reversion was an increasing function of the level of mispricing in the previous period (arbitrage induced), mean reversion increased as the time to maturity decreased (decreasing arbitrage risk and time to maturity is not a surrogate for thin trading in stocks), and U-shaped intraday patterns in mean reversion were correlated with trading volume (trading volume is an inverse proxy for infrequent trading).

Yadav and Pope (1993b) also analysed the mean reversion in the time series of spread mispricing. A spread arbitrage is the simultaneous buying and selling of futures contracts with different delivery dates. The analysis of calendar spreads overcomes a number of microstructure impediments inherent in modelling the related cash/futures mispricing series. For example, the behaviour of the spread mispricing should be unrelated to measurement errors such as the infrequent trading effect in the stock index, restrictions on short sales, and execution lag associated with implementing the arbitrage spread. Yadav and Pope found that the absolute value of spread mispricing often exceeded theoretical transaction cost boundaries and there was a high degree of persistence in mispricing. Moreover, trading strategies which incorporated short term spreads, and were triggered by over and under priced far futures contracts, earned significant positive and negative

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9 The analysis of spread mispricing for gold futures contracts in Australia has been analysed by Hodgson and Barrack (1992).
returns. With relation to mean reversion the first order autoregressive parameter for the change in mispricing was -0.492. This high and negative parameter, in a market place which does not have thin trading because the arbitrage is undertaken between two futures contracts, gave strong support for an arbitrage induced explanation for mean reversion in the mispricing series.

3.6 SUMMARY

The stylised findings from the empirical research into the microstructure of the stock and futures markets and the impact of feedback between the two markets is now summarised.

(i) The majority of evidence regarding time of the day effects in stock and futures markets documents a U-shaped curve in returns, volatility, autocorrelations and volume over the course of the trading day. Explanations revolve around information or trading structure theories. Mid day trading halts induce higher volatility before and after the break.

(ii) Trading time prices are significantly more volatile than non-trading time prices. This feature has been related to the release of public information over the non-trading period and the release of private information through intraday trading.

(iii) The liquidity and depth of the market appears to affect the formation of prices. There is a slower price reaction for smaller firms in stock markets, the autocorrelation of prices changes from weakly positive to strongly negative as futures contracts mature, and there is a strong correlation between trading volume and serial correlation.

(iv) The psychology and trading clientele of the market may have an impact on intraday price patterns. Patterns differ between bull and bear markets in Japan, there is a consistently more negative nontrading weekend returns in stock markets compared to futures markets, trading time returns differ between stock and futures, and intraday volatilities are consistently higher in futures compared to stock markets.
(v) There is strong positive first order autocorrelation in stock markets and weak negative first order autocorrelation in futures. This feature has been related to nonsynchronous trading in stock markets. There is little difference, however, in first order autocorrelation of stock and futures prices in Asian markets.

(vi) A strong contemporaneous relationship exists in price innovations between futures and stock price movements. Earlier research suggests that the futures market is more likely to display price leadership than the stock market. This is explained in terms of the transactional and liquidity efficiency of futures markets and the transfer of information from the futures to the stock market.

(vii) Research which has indicated short term price leadership in the futures market, documented consistently higher volatility in the futures market, and short term volatility increases has been interpreted as evidence that the futures market causes volatility spillover into the cash market. The evidence on the long term effects on volatility suggests that the introduction of derivative futures trading does not have any undue effects on the volatility of underlying cash market.

(viii) There are consistent intraday arbitrage opportunities between futures and stock markets. The arbitrage mispricing series shows strong and persistent positive autocorrelation and negative autocorrelation in the first difference.

(ix) There is some contention over the cause of the negative autocorrelation or mean reversion in the arbitrage mispricing series. A number of authors proposed that the mean reversion is caused by the rational actions of arbitrageurs who trade the cost of carry relationship. On the other hand, Miller, Muthuswamy and Whaley (1994) have argued that the mean reversion is a statistical illusion caused by thin trading in the underlying stocks and is not explained by arbitrage.
CHAPTER FOUR

INFORMATION TRANSFER, MICROSTRUCTURES AND INTRADAY PRICE RETURN SPIKES

4.1 INTRODUCTION

Information affects markets. The litany of research aimed at determining the 'informational efficiency' of security markets bears testimony to the belief in this statement by accounting and finance researchers. But precisely how information affects the beliefs of market participants and how information is disseminated into prices, is still not well understood.

In recent years there has been a growing research interest in the microstructure of markets and the international linkages across markets. The finer analysis applied by these research programs offers the prospect of a more in depth understanding of the 'beehive' like activity of markets, and especially the prospect of filtering out and dissecting the impact of information on prices. The review in chapter three documents the existence of persistent interday and intraday price patterns in equity and futures markets, particularly those traded in the US. In brief there are spikes in returns, volatility and trading volume at the closing and opening of trading, with the intraday evolution following a rough U-shaped pattern [Wood, McInish and Ord (1985), Harris (1986), Amihud and Mendelson (1987), McInish and Wood (1991) and Ekman (1992)]. There is also some tendency for price reversals to be more common in the first half hour of trading and they are accentuated in 'bull' periods [Amihud and Mendelson (1991b), Chang, Fukuda, Rhee and Takano (1993)].
A cross-section of theories has emerged which seeks to explain these patterns in terms of the flow of information over the course of the trading day. French and Roll (1986) first suggested that price changes can be induced by: (i) the release of public information; (ii) the release of private information through the trading activities of informed investors; and (iii) the effects of noise traders. The rational information models of Admati and Pfleiderer (1988), Foster and Viswanathan (1990) and others, predict that price changes will cluster according to the release of private information through trading. Other information models predict that prices overreact to current information and mean-revert back to a fundamental value after a price jump [DeBondt and Thaler (1989)], or there is price herding in the short term [Froot, Scharfstein and Stein (1992)]. In summary, explanations range from the cognitive psychology view which suggests that investors tend to overweight the value of current information, the existence of noise traders who trade on the same information and induce information spillovers and self-fulfilling expectations, through to the contention that expected returns vary through time consistent with varying risk premiums.

A number of other factors have also been put forward as explanations of opening price spikes and other intraday price patterns including: (i) opening price setting mechanisms such as call auctions; (ii) trading procedures such as open outcry versus electronic trading; (iii) quote driven versus order driven price setting (iv) non-synchronous trading in thin stocks on intraday indices; (v) speculative activity which is attracted to specific markets; and (vi) sample specific and/or market specific anomalies.

The primary objective of this chapter is to identify and determine the dynamic effects of publicly available overnight information on separate intraday stock and future price returns by applying intervention and transfer function time series models. These models have a number of advantages. First, they are extensions of classical econometric models which incorporate the effect of information interventions and allow for explicit contemporaneous relationships among the endogeneous time series. Secondly, the modelling process is flexible and the transfer function can be specified to capture the effects on the time series in a variety of ways. For example, step functions, pulse functions, or oscillating impact
functions may be used to test for immediate impounding, decaying reaction or overreaction to information. Previous applications have tested the impact of a wide range of economic interventions such as consumer prices and atmospheric pollution [Box and Tiao (1975)], the influence of promotions on sales, the changing price structure in the US telephone industry, and increased competition between rail and air on London to Scotland passenger routes [Jenkins and McLeod (1982)]. The impact of seat belt legislation on traffic accidents has also been analysed in Queensland, Australia by Bhattacharyaa and Layton (1979). It, therefore, seems logical to apply this modelling approach to stock and futures markets which are subject to impacts from a wide range of public and private information.

This chapter applies intraday price data from the AOI to test for the impact of information accruing from the previous day's price change on the Dow Jones 65 Stock Composite Index (DJ65). As an additional test, intraday returns for the SPI futures contract were also analysed in order to provide a control and a comparison on a number of structural features which are unique to the Australian environment. First, the use of the SPI contract provides a control for information impact because it opens ten minutes earlier than the stock market. Second, in addition to the inherent differences between trading procedures in equity and futures markets (screen trading versus open outcry), opening prices of Australian equities are set by a system which is lagged over short intervals and effectively halts trading for this period. Furthermore, the futures market has a trading halt by closing for lunch from 1230 through to 1400 every day whilst the equity market continues trading, and overnight trading occurs in the futures but not in equities. Finally, the equity market experiences pronounced nonsynchronous trading with only about thirty stocks traded on a continuous basis throughout the day [Hathaway (1986)].

These unique microstructure features provide an incentive to extend the previous research, which has concentrated on larger well traded specialist markets, into the smaller order driven Australian market. Therefore, a secondary motive of this chapter is to document and compare the intraday evolution of prices which are affected by different trading
structures and thinly traded conditions. In brief, it is found that unadjusted equity and futures price returns in Australia evolve in consistent and distinct patterns over the course of the trading day. After adjusting for nonsynchronous trading and filtering out the overnight information impacts from the US market a number of features emerge. Firstly, these factors do not fully account for the early morning price return spikes. Secondly, a similar pattern in both markets remains with a positive price return spike at 1000 followed by a roughly equal negative price return at 1015. This opening pattern remains in both markets even though they have different trading microstructures. Thirdly, information is transferred into prices in different ways in the two markets. Some of the statistical results are consistent with rational explanations of market efficiency, whilst other results support an overreaction/psychological viewpoint of market behaviour. In general the analysis suggests that more complex and dynamic theories are required to explain the processes of intraday price behaviour.

4.2 BACKGROUND

4.2.1 Intraday Price Returns

A number of researchers have studied intraday price returns in cash and futures index markets. Harris (1986), used 15 minute return data on stocks from the New York Stock Exchange (NYSE) and found that prices did not evolve at a uniform rate throughout the day. Returns (except Monday) showed a U-shaped pattern with returns in the first and last hour of trade greater than those observed during the rest of the day. Chang, Fukuda, Ghon Rhee and Takano (1993) undertook a similar study of the TOPIX index in Japan. This study was distinguished by two factors. The Japanese stock market closes from 1100 to 1300 and the study tested for different return patterns in bull and bear periods. The results showed that intraday trading halts induced negative returns before and after the lunch break. Further, opening returns during bull periods were highly positive whilst they were negative during bear periods. This suggested that the nature of opening returns may vary with different information or market ‘moods’.
Changes in the prices of futures markets have shown similar patterns in a number of studies. Finnerty and Park (1988) found a U-shaped pattern in MMI futures price returns. Ekman (1992) observed that the absolute value of returns was up to three times higher at open and two times higher at close for the Standard and Poor's (S&P) 500 Index futures market. Yadav and Pope (1992) using hourly cash and futures data from the FTSE 100 index from 1986 to 1990, also found that prices tend to rise systematically during the first hour of trading even though the UK has a different trading structure.

There are also some differential price patterns between cash and futures returns. Finnerty and Park (1988) discovered that the negative weekend effect in stock markets starts to occur from about 1330 on Friday, but this is not the case in futures markets. Yadav and Pope (1992) found that the London stock market rises when the market is open but the futures market rises when the market is closed. In the US, the first order autocorrelations of intraday cash index stock returns are high and positive, but for futures they are low and negative [MacKinlay and Ramaswamy (1988), Cheung and Ng (1990), Chan, Chan and Karolyi (1991)]. In Asian markets there is little difference between cash and futures with autocorrelations not significantly different from zero [Lim (1992), Ho, Fang and Woo (1992)].

A number of the above studies have suggested that the relatively high price returns early in the day may be attributed to overnight public information released since the previous day's close. Jordan, Seale, Dinehart and Kenyon (1988), however, suggested that the increased price activity towards the close of trading could not be wholly attributed to the flow in information, but may partially be due to speculators who did not wish to hold open overnight positions. Herbst and Maberly (1992) took a different perspective and argued that the later closure of the futures market, compared to the cash market, enabled the futures market to play an important price discovery role associated with information gathering. They hypothesised that informed traders would gather information during the course of the trading day and choose to trade on that information after the close of the cash market and before the close of futures trading. They concluded that the increased activity
at the end of the day in futures prices was a function of the flow of private information and was correlated to the change in opening prices on the next day's cash market.

A number of the research issues analysed in this chapter are related to the above discussion. For example, whether the intraday return patterns in Australia are similar to the U-shaped patterns observed in other markets, whether there is any difference between intraday returns or in the autocorrelation structures between cash and futures, and what role does overnight information play in the explanation of opening return spikes. In addition, the process by which information is impacted and transferred across subsequent prices is also analysed. This analysis encompasses a number of possible information theories which are briefly summarised below.

**4.2.2 Information Transfer - Rationality or Overreaction**

One negative heuristic held by a number of researchers in financial economics is that financial markets are 'efficient' in that prices reflect all available information. An extreme form of this efficient market hypothesis (EMH) implies that when a new piece of information becomes publicly available, it is instantaneously impounded into security prices. A lag in the price adjustment or a slow transfer of information into prices, under this strict form of market efficiency, would not exist. This approach also assumes that traders calculate the price of a security over long time horizons with short-term speculators having little influence.

A rational explanation for any slow diffusion of information into prices has been proposed by Kyle (1985) and extended by Admati and Pfleiderer (1988). This hypothesis predicts that different intraday price patterns are associated with private information traders. The model assumes asymmetric information and a market place consisting of four types of traders. First, private information traders who trade on information which is generally not observed by the market. The volatility of the price signal reflects the precision of the information set they hold. Secondly, uninformed non-discretionary liquidity traders who trade for exogenous liquidity purposes unrelated to information about future prices.
Thirdly, noise traders who trade on an information set unrelated to fundamentals and orthogonal to the private information set. Fourthly, discretionary liquidity traders who do not hold private information but who rationally use order flow to learn private information, and hence, generate expectations about future prices.

Private information traders will trade when transaction costs are lowest (in periods of high trading volume), which provides the opportunity to disguise their trades and maximise the return from holding private information. In turn, these informed prices reveal enough information to make the trading costs of uninformed liquidity traders the lowest at this time. Consequently, both informed and uninformed traders choose to trade simultaneously. The Admati and Pfleiderer model predicts that in periods of high trading volume we should observe periods of high volatility and clustering of information release through price effects.

Other researchers hypothesise that the market is not instantaneously rational in the way it incorporates information into prices. The idea that prices mean-revert in predictable patterns to some fundamental value after information shocks has been put forward by Bremer and Sweeney (1988), Lehmann (1988) and Fama and French (1988). They document evidence of predictable reversion patterns for stocks that have one day price jumps or are classified as 'winners' or 'losers'. Porterba and Summers (1988) found mean-reverting price behaviour in a number of countries outside the USA and suggested that the patterns were stronger in smaller less developed stock markets. DeBondt and Thaler (1989) further suggested that investors systematically overreact to current information. DeBondt and Thaler documented evidence of contrarian strategies which are successful because of systematic investor overreaction.

Froot, Scharfstein and Stein (1992) proposed that traders have short-term investment horizons and tend to focus on one source of information. This hypothesis is driven by positive information spillovers: as more speculators study a given piece of information, more of that information disseminates into the market, and therefore, the profits from learning that information early increase. The assumption of a short-term investment
horizon means that traders tend to focus (or herd) on single pieces of information, rather than on a diverse set of data which may include long-term fundamental information.

Finally, has been proposed [Silber (1984), Veljanovski (1986), Berkowitz, Logue and Noser (1988)] that index futures prices incorporate information at a faster rate because they have a comparative advantage in transaction and liquidity costs. These microstructure features also predict differences between the type of information which flows to stock and index futures markets. For example, Kumar and Seppi (1989), Chan (1990), and Subrahmanyam (1991) showed that fixed costs of trading, budget constraints, and different expected profits caused traders in futures markets to collect more marketwide information and traders in cash markets to collect more firm specific information.

These diverse information theories form the basis for the determination of appropriate mathematical and statistical tests in section 4.4 for the testing of the impact from overnight information and the transfer effects into subsequent prices. Other factors such as trading microstructures have also been put forward as explanations for intraday price patterns and these are briefly summarised in the next section.

### 4.2.3 Trading Microstructures

Amihud and Mendelson (1991b) concluded that the form of the opening trading mechanism affects the pattern of price returns and influences the price discovery process. Specifically, a clearing transaction is more efficient than a market which opens with continuous trading. Trading halts or lagged price setting structures have also been hypothesised to affect price evolution in financial markets. Greenwald and Stein (1991) contend that trading halts have a calming influence on prices, whilst others suggest that they increase uncertainty and price setting is less stable under these conditions (Gerety and Mulherin, 1992).

Special priority trading rules are applied to the opening of the ASE whereby the normal continuous auction procedure is suspended and prices are set by matching prior bids and
offers (see appendix 2.1 for a full description). This staggered opening procedure represents a suspension of trading in the equity market whereas the futures market continues as an open outcry market. This feature enables a comparison to be made with the futures prices during the opening period in the spirit of Amihud and Mendelson. Further, the futures market opens and closes ten minutes earlier and later than the stock market and suspends trading over lunch from 1230 to 1400.

Thin trading and bid/ask bounce have also been found to affect intraday prices. Infrequent trading of stocks which comprise the AOI means that the computed index value will probably incorporate some prices which are stale. Besides infrequent trading individual security returns may be influenced by the splitting of large buy and sell orders into two or more smaller orders. This is more likely to occur in smaller markets where participants have monopoly power or access to insider information. Possible contamination of futures returns may also arise from the random bouncing of transaction prices between bid and ask levels which produces negative first order correlation [Roll (1984)]. These microstructure effects, therefore, are more likely to induce positive first order autocorrelation in the AOI, and negative first order autocorrelation in the SPI.

These features will be analysed in later sections and the potential affects taken into account when the transfer function time series model is formulated. The next section describes the data set and reports preliminary descriptive statistics.

4.3 DATA AND DESCRIPTIVE ANALYSIS

4.3.1 Data

The data used consisted of 15 minute interval 'snapshot' prices obtained from a commercial organisation over the period 1 April 1992 to 30 March 1993 for the SPI futures contract and the AOI. This data was checked for integrity against 15-minute intraday data on the AOI in hard copy form and tick-by-tick data on the SPI, obtained from the stock and futures exchanges. Particular attention was paid to checking prices
around the trading breaks at the opening and closing of daily trading and around lunchtime.

The SPI futures market consists of a number of contracts maturing at three monthly intervals - March, June, September and December. The nearest traded futures contract was used to match against the AOI because the trading volume in further futures contracts was relatively thin and hence prices could be unreliable. The SPI trades from 0950 to 1610 each day (with a break for lunch from 1230 to 1400), and the shares which constitute the AOI trade continuously from 1000 to 1600. The observations for the first and last ten minutes of trading were included for the SPI futures but the lunch-time trades from 1245 to 1345 excluded for the AOI. Three days were deleted from the sample - 3 August 1992 because no trading data could be obtained for the SPI, 24 August 1992 because there was no trading on the stock market during the morning, and 9 February 1993 because prices were extremely erratic and deemed to be aberrant. This gave 20 (22) observations during the day for the AOI (SPI), for 249 complete trading days with a total of 4980 (5478) observations for the AOI (SPI) over the research period.

A number of tests compare the rate of return for the indices during different periods throughout the day. Strictly speaking there is no actual rate of return for futures indices as most trading is carried out on the basis of a margin deposit which varies according to time specific trading conditions. As an alternate description the rate of return can also be viewed as a measure of the rate of change in prices. The logarithm of the price relative ($\eta_t$) was then calculated as follows:

$$\eta_t = \ln(P_t) - \ln(P_{t-1})$$

(4.1)

where $P_t$ is the price observed at time $t$, $P_{t-1}$ is the previous period's price and $\ln$ is the natural logarithm. For the most part $\eta_t$ represents a fifteen minute return. For example, $\eta_{1015}$ is a fifteen minute return between 1000 and 1015. There are, however, a few exceptions. For the AOI $\eta_{1000}$ represents an overnight non-trading period return computed using the morning opening AOI price and the previous day's closing AOI price.
For the SPI, $\eta_{0950}$ represents the overnight non-trading period return. Over the lunch period there is no trading on the futures market floor and $\eta_{1400}$ represents the return over this non-trading period. For the AOI trading is continuous over the lunch period so $\eta_{1400}$ represents a one and a half hour period return. The first and last trading time returns for the SPI futures contract ($\eta_{1000}, \eta_{1610}$) are ten minute returns.

4.3.2 Descriptive Statistics

The year of the study, from 1 April 1992 to 30 March 1993, may be described as a relatively stable period with the AOI index increasing in value by some 5.24% from 1584.4 to 1667.4. Descriptive statistics for the entire return series are reported in Table 4.1. The AOI mean return was slightly higher than the SPI and had a higher excess kurtosis and slight negative skewness, but neither series was statistically different from zero using t-tests. The most notable difference between the two series was that the standard deviation of the SPI series was some 52% higher than the AOI series.

<table>
<thead>
<tr>
<th>Table 4.1</th>
<th>DESCRIPTIVE STATISTICS AOI AND SPI INTRADAY RETURN SERIES</th>
</tr>
</thead>
<tbody>
<tr>
<td>AOI</td>
<td>SPI</td>
</tr>
<tr>
<td>Number</td>
<td>4980</td>
</tr>
<tr>
<td>Mean</td>
<td>0.00000097</td>
</tr>
<tr>
<td>t-statistic</td>
<td>0.51</td>
</tr>
<tr>
<td>Adjusted t-statistic*</td>
<td>0.36</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0013510</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.06560</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>15.94</td>
</tr>
</tbody>
</table>

* t-statistic adjusted for autoregressive time series process

The stock and futures return series were also tested for nonstationary using augmented Dicker-Fuller tests\(^1\). The null hypothesis of a unit root ($\phi = 0$) was rejected for both the stock and futures return series with test statistics of -18.69 for the stock series and -20.14 for the futures series against a critical value of -2.57 [Dickey and Fuller, 1981, p. 1062-]

\(^1\) The model applied was in the form $\Delta \eta_t = \phi \eta_{t-1} + \beta_o + \sum_{g=1}^{p} \beta_g \Delta \eta_{t-g} + \varepsilon_t$; terms are added until the estimated regression residuals $\varepsilon_t$ are purged of significant serial correlation. A deterministic time trend was also added to the above model. This had no significant effect on the results.
This result confirms that the two series do not need any differencing, they are stationary I(0) series and standard time series analysis can now be applied.  

In Table 4.2 the descriptive statistics are decomposed into intraday periods averaged over all days and Figure 4.1 plot average returns, cumulative returns, skewness and excess kurtosis. Volatility is relatively higher in the mornings for both markets and the futures market has a consistently higher volatility than the stock market. Excess kurtosis has an inverted U-shaped pattern with the highest points in both markets before and after the lunch break. This pattern is opposite to trading volume and suggests that periods of inactivity flatten the return distribution.

As a preliminary statistical test for the existence of intraday price spikes the equality of mean returns across intraday trading intervals for each weekday and within an interval across all weekdays were tested by applying F-statistics computed from dummy variable regressions. This test has been previously applied by other researchers [Harris (1986), Finnerty and Park (1988), Yadav and Pope (1992) and Ekman (1992)] to determine the statistical significance of intraday price return spikes in stock and futures markets. As a further comparison the robustness of the F-tests was also investigated by applying robust regressions and the non-parametric Kruskal-Wallis test. It should be noted, however, that in computing standard errors these tests ignore any autocorrelation structure in the price return series, which if significant, could give false tests results. The purpose of undertaking this preliminary analysis was to provide a comparison with previous research and as a first up unconditional indication of intraday price return spikes. The transfer function time series model, developed in the next section, provides a filtering process.

If a time series $\eta_t$ is I(0), then it is stationary, whereas if it is I(1) its change, $\Delta \eta_t$ is stationary. If $\eta_t \sim I(0)$ and has a zero mean then: i) the variance of $\eta_t$ is finite, ii) an innovation has only a temporary effect on the value of $\eta_t$, iii) the expected length of times between crossings of $\eta = 0$ is finite, iv) the autocorrelations, $\rho_k$ decrease steadily in magnitude for large enough $k$, so that their sum is finite.

The weighting scheme used for the robust regressions was computed by weighting each observation, $t$, by $(1/(t + \epsilon_t^2))$ where $\epsilon_t^2$ is the squared residual from dummy variable regressions. This technique is similar in concept to a number of weighting schemes suggested in the literature (see Judge, Hill, Griffiths, Lutkepohl and Lee, 1988, Ch.22.4) and is designed to adjust for leptokurtic distributions.
which provides unbiased test statistics. The results (reported in table 4.2) indicate significant differences in mean returns at the opening of trading through to 1030 in both markets, the existence of a negative spike in mid-afternoon, and a positive return at the close of trading. There was no difference between intraday mean returns across weekdays indicating no day of the week return effects during the time period of the study.

There are a number of other points to note about the unconditional returns in the two markets at different times of the day. There are two large and positive opening return spikes in the futures market at 0950 (0.000333) and 1000 (0.000435), but only one in the stock market at 1000 opening (0.000428). These larger positive returns are similar to the results of Harris (1986), Yadav and Pope (1992) and Ekman (1992) who observed significantly larger and positive overnight and first hour returns in markets with different opening price setting mechanisms and trading structures. One significant difference observed in Australian markets is that these positive returns are then followed by negative returns at 1015 and 1030 which, in effect, eliminates the positive overnight return in the stock market but does not completely reverse the early positive returns in the futures market. The cumulative returns plotted in figure 4.2 Panel B give a further insight and show that futures returns outperform the equity market in the morning with the roles reversed in the afternoon. One further observation is that once the overnight return is removed then cumulative intraday trading time returns in Australia are negative. This could signify the arrival of negative information during Australian trading hours or a slow mean reversion because of an overreaction to overnight information.

The lunch break and the period immediately afterward is also interesting in that, on average, returns drop to a negative value straight after lunch and then revert to zero at about 1500 after reaching a low point at 1430. This mid-afternoon phenomena had been previously documented by Harris (1986) who observed a price decline between 1430 and 1515 on US stock data, and Yadav and Pope (1992) who found that mean and median stock and futures prices between 1400 and 1500 in the UK were negative and significantly different from average prices over other intervals. Yadav and Pope suggested that one
explanation for the mid-afternoon fall in UK prices was a contagion effect caused by the opening of the US market which caused a price correction in the UK market. The observation that Australian markets display a similar pattern suggests that this intraday seasonality may be independent of any contagion effect.

Table 4.2
DESCRIPTIVE STATISTICS
INTRADAY AOI AND SPI UNCONDITIONAL RETURNS

<table>
<thead>
<tr>
<th>Panel A - AOI Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>TIME</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>1000</td>
</tr>
<tr>
<td>1015</td>
</tr>
<tr>
<td>1030</td>
</tr>
<tr>
<td>1045</td>
</tr>
<tr>
<td>1100</td>
</tr>
<tr>
<td>1115</td>
</tr>
<tr>
<td>1130</td>
</tr>
<tr>
<td>1145</td>
</tr>
<tr>
<td>1200</td>
</tr>
<tr>
<td>1215</td>
</tr>
<tr>
<td>1230</td>
</tr>
<tr>
<td>1400</td>
</tr>
<tr>
<td>1415</td>
</tr>
<tr>
<td>1430</td>
</tr>
<tr>
<td>1445</td>
</tr>
<tr>
<td>1500</td>
</tr>
<tr>
<td>1515</td>
</tr>
<tr>
<td>1530</td>
</tr>
<tr>
<td>1545</td>
</tr>
<tr>
<td>1600</td>
</tr>
</tbody>
</table>

* Return multiplied by 100

The F statistic tests whether intraday means are equal across weekdays (F days) and within the trading day (F trading). Individual F statistics (e.g. F0950, F1600 etc.) tests whether each mean is equal to the remaining trading time means. The F statistics are calculated from dummy variable ANOVA regressions and robust regressions. The weighting scheme used for the robust regressions was computed by weighting each observation, t, by (1/(1 +堆**2)) where 堆**2 is the squared residual from the ANOVA dummy variable regressions. The non-parametric Kruskal-Wallis (K-W) statistic tests for differences in the medians of all trading times. The probability that the means or medians are equal is reported in brackets. It should be noted that these descriptive tests do not account for any possible dependencies in the data. An approach which accounts for this is presented in the next section.
Table 4.2 (cont’d)

<table>
<thead>
<tr>
<th>TIME</th>
<th>RETURN*</th>
<th>T for H₀: ( \text{Return}=0 )</th>
<th>STDEV</th>
<th>SKEWNESS</th>
<th>EXCESS KURTOSIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>0950</td>
<td>0.0333</td>
<td>2.74</td>
<td>0.577</td>
<td>-0.432</td>
<td>2.473</td>
</tr>
<tr>
<td>1000</td>
<td>0.0435</td>
<td>3.34</td>
<td>0.209</td>
<td>-0.277</td>
<td>0.449</td>
</tr>
<tr>
<td>1015</td>
<td>-0.0312</td>
<td>-2.39</td>
<td>0.239</td>
<td>-0.004</td>
<td>0.784</td>
</tr>
<tr>
<td>1030</td>
<td>-0.0219</td>
<td>-1.68</td>
<td>0.221</td>
<td>-0.302</td>
<td>1.211</td>
</tr>
<tr>
<td>1045</td>
<td>-0.0099</td>
<td>-0.07</td>
<td>0.198</td>
<td>-0.120</td>
<td>1.394</td>
</tr>
<tr>
<td>1100</td>
<td>-0.0048</td>
<td>-0.37</td>
<td>0.191</td>
<td>-0.676</td>
<td>2.210</td>
</tr>
<tr>
<td>1115</td>
<td>0.0035</td>
<td>0.27</td>
<td>0.176</td>
<td>-0.080</td>
<td>1.809</td>
</tr>
<tr>
<td>1130</td>
<td>0.0035</td>
<td>0.27</td>
<td>0.173</td>
<td>0.234</td>
<td>2.333</td>
</tr>
<tr>
<td>1145</td>
<td>0.0103</td>
<td>0.79</td>
<td>0.181</td>
<td>0.074</td>
<td>1.803</td>
</tr>
<tr>
<td>1200</td>
<td>0.0008</td>
<td>0.06</td>
<td>0.153</td>
<td>-0.183</td>
<td>1.147</td>
</tr>
<tr>
<td>1215</td>
<td>-0.0040</td>
<td>-0.31</td>
<td>0.146</td>
<td>-0.428</td>
<td>1.204</td>
</tr>
<tr>
<td>1230</td>
<td>0.0154</td>
<td>1.18</td>
<td>0.142</td>
<td>0.305</td>
<td>3.868</td>
</tr>
<tr>
<td>1400</td>
<td>-0.0041</td>
<td>-0.32</td>
<td>0.144</td>
<td>0.503</td>
<td>6.236</td>
</tr>
<tr>
<td>1415</td>
<td>-0.0150</td>
<td>-1.15</td>
<td>0.166</td>
<td>-0.856</td>
<td>5.993</td>
</tr>
<tr>
<td>1430</td>
<td>-0.0263</td>
<td>-2.01</td>
<td>0.166</td>
<td>-0.780</td>
<td>6.401</td>
</tr>
<tr>
<td>1445</td>
<td>-0.0033</td>
<td>-0.25</td>
<td>0.166</td>
<td>-0.550</td>
<td>2.218</td>
</tr>
<tr>
<td>1500</td>
<td>0.0002</td>
<td>0.01</td>
<td>0.147</td>
<td>0.615</td>
<td>3.231</td>
</tr>
<tr>
<td>1515</td>
<td>0.0001</td>
<td>0.01</td>
<td>0.151</td>
<td>-0.181</td>
<td>1.005</td>
</tr>
<tr>
<td>1550</td>
<td>0.0004</td>
<td>0.03</td>
<td>0.149</td>
<td>0.156</td>
<td>0.787</td>
</tr>
<tr>
<td>1545</td>
<td>0.0053</td>
<td>0.40</td>
<td>0.151</td>
<td>-0.395</td>
<td>1.187</td>
</tr>
<tr>
<td>1600</td>
<td>-0.0051</td>
<td>-0.39</td>
<td>0.146</td>
<td>0.278</td>
<td>1.733</td>
</tr>
<tr>
<td>1610</td>
<td>0.0180</td>
<td>1.38</td>
<td>0.177</td>
<td>-0.071</td>
<td>1.035</td>
</tr>
</tbody>
</table>

* Return multiplied by 100

<table>
<thead>
<tr>
<th></th>
<th>Anova</th>
<th>Robust</th>
<th>Kruskal-Wallis</th>
</tr>
</thead>
<tbody>
<tr>
<td>F Days</td>
<td>0.38 (0.86)</td>
<td>0.37 (0.87)</td>
<td>0.85 (0.93)</td>
</tr>
<tr>
<td>F Trading</td>
<td>2.00 (0.00)</td>
<td>2.17 (0.00)</td>
<td>46.23 (0.00)</td>
</tr>
<tr>
<td>F 0950</td>
<td>7.45 (0.01)</td>
<td>7.94 (0.01)</td>
<td></td>
</tr>
<tr>
<td>F 1000</td>
<td>17.77 (0.00)</td>
<td>20.62 (0.00)</td>
<td></td>
</tr>
<tr>
<td>F 1015</td>
<td>7.63 (0.01)</td>
<td>8.56 (0.01)</td>
<td></td>
</tr>
<tr>
<td>F 1430</td>
<td>4.39 (0.04)</td>
<td>4.45 (0.04)</td>
<td></td>
</tr>
<tr>
<td>F 1610</td>
<td>3.78 (0.05)</td>
<td>4.08 (0.04)</td>
<td></td>
</tr>
</tbody>
</table>

There is a relatively large difference between cash and futures returns at close of AOI trading at 1600 with AOI returns positive and SPI returns negative. After the stock market closes at 1600 the futures market recovers somewhat and posts a positive 0.00018 return in the next 10 minutes. This divergence is similar to that observed by Yadav and Pope (1992) who found a 0.015% return spike in the last hour of the cash market and a -0.028% negative spike in the futures. The divergence is not consistent with cogent explanations of market behaviour unless the two markets can be viewed as segmented during this period. However, it is consistent with segmented market arguments that passive index tracking portfolio managers tend to trade in the cash market towards the end of the day⁴ [Brock and Kleidon (1989)] and therefore cash prices rise due to excess

⁴ To minimise tracking error since mutual funds are valued at closing prices.
Panel A - Returns

Panel B - Cumulative returns

Panel C - Skewness of returns

Panel D - Kurtosis of returns

* Return multiplied by 100

Figure 4.1 Intraday descriptive figures for AOI and SPI returns.
demand. On the other hand, if the futures market consists of an excess of traders who are unwilling to hold open positions overnight or an excess of speculative long day traders, then we would expect intraday differences in price returns towards the close of trading. As a preliminary unconditional analysis these results suggest some trading strategies which differ between markets, but regardless of the individual variations in the separate markets, cumulative returns are very similar at the end of the day.

4.4 MODELS APPLIED

In the microstructure literature there is substantial evidence of systematic price behaviour in the short run pattern of price returns, and the preliminary analysis in the above section establishes the possibility of systematic patterns in the Australian market. This section develops an econometric model that incorporates the various theories of market microstructure and information impact. The model has a number of components. An intervention which describes the impact of overnight information on opening returns, transfer functions which model the short run impact of information or price spikes on subsequent returns, an autoregressive component, and finally dummy variables which model the fixed time of the day effects.

The building of a transfer function time series model allows the examination of a number of research questions, for example: How does overnight information impact on opening price returns? Is it instantaneous or is there a lag or overreaction effect? Is the impact different between markets with diverse trading structures? Do intraday price return spikes affect subsequent returns?

Theoretically this approach is also more defensible on a number of points. First, by filtering out the impact of public overnight information only the endogenous spikes (if any) will remain. This controls, somewhat, for such arguments as the 'Monday morning effect' is caused by the accrual of negative information over the weekend. Secondly, by
adjusting the model for the autoregressive components and deriving a model with 'white noise' residuals, the resultant statistical inferences take account of the dependent nature of the data. This allows the researcher to more truly establish the existence and likely cause of intraday price return patterns. The following sections build up and outline the intervention and transfer function components of the model.

4.4.1 Interventions

In the analysis of the time series of stock and futures prices, relatively little attention has been paid to incorporating the impact of exogenous interventions into the endogenous time series. However, it is well known that these markets are frequently affected by shocks\(^5\) that can affect a time series in several ways. They can change the level, either abruptly or after some delay, change the trend, and have either a permanent or transient impact. In the case of intraday research, whereby the timing of exogenous interventions (such as overnight information) on the return series is known, then a transfer function model which takes account of an intervention may be postulated as:

\[
\eta_t = \nu(B) I_t + N_t
\]  

\((4.2)\)

I\(_t\) is the intervention (input) variable, and is a 'dummy' or 'indicator' variable taking the values 1 and 0 to denote the occurrence or non occurrence of the exogenous intervention. \(\eta_t\) is the endogeneous return series and \(\nu(B)\) is a (possibly infinite) polynomial which may admit a number of rational forms. For example, one form of the lag polynomial:

\[
\nu(B) = \frac{\omega(B)^b}{\delta(B)}
\]  

\((4.3)\)

allows \(I\) to influence \(\eta\) via a distributed lag \(\nu(B)\) which is referred to as the transfer function and the numerator and denominator polynomials are defined as:

\(^5\) The October 1987 stock market crash is an obvious example.
\[ \omega(B) = \omega_0 - \omega_1 B - \ldots - \omega_8 B^8 \]

and

\[ \delta(B) = 1 - \delta_1 B - \ldots - \delta_r B^r \]

The parameter \( b \) is referred to as the dead-time of the model. If \( b = 0 \) then there is a contemporaneous relationship, but if \( b > 0 \) then there is a delay of \( b \) periods before \( I_t \) begins to influence \( \eta_t \).

A variety of forms may be hypothesised for the impact of the input series \( I_t \) and the specification of \( \varphi(B) \) at time \( T \). For example:

a) A pulse variable, which models an intervention which has a one-off impact on \( \eta_t \) at time \( T \),

\[ I_t = \xi_t^{(T)} , \text{ where } \xi_t^{(T)} = \begin{cases} 1, & t = T \\ 0, & t \neq T \end{cases} \]

b) A step variable, which models a permanent change in \( \eta_t \) at observation \( T \),

\[ I_t = \xi_t^{(T)} , \text{ where } \xi_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \]

c) A pulse input which describes the case in which \( I_t \) has a transient effect on \( \eta_t \) via the transfer function \( \varphi(B) \) and admits the possibility of a residual impact across subsequent prices.

\[ \varphi(B) = \frac{\omega}{1 - \delta B} \]

where \( \omega \) measures the initial increase and \( \delta \) the rate of decline. These models can be extended to represent a variety of effects. For example, if \( \delta \) in (c) above is zero, then an instantaneous impact occurs, but if \( \delta \) is equal to one then the impact is permanent. These models are further developed in the next section and related to various information impact theories from the area of financial economics.
The relationship between $\eta$ and $I$ is generally not deterministic and will be contaminated by noise. This is captured by the endogeneous process $\eta_t$ which will usually be serially correlated. A major assumption used in transfer function noise modelling is that $\eta$ and $I$ are independent, which rules out feedback from $\eta$ to $I$ (I can influence future $\eta$'s but not vice-versa). One further assumption is that the bivariate stochastic process $(\eta_t, I_t)$ is jointly stationary and Box and Jenkins (1976, Ch.11) emphasise the need to establish that all the time series being considered, both output and input, are stationary. This, by a simple extension of the analysis of univariate time series, enables sample autocorrelation and cross-correlation functions to be usefully employed in model identification. As a prerequisite, it therefore must be determined whether $\eta_t$ and $I_t$ are stationary processes. Pragmatically this is equivalent to determining whether $\eta_t$ and $I_t$ contain unit roots.6

4.4.2 Transfer Functions Related to Information Theories

The next step was to prespecify three possible intervention and transfer function models which have theoretical antecedents in the financial literature. The objective was to identify the process(es) whereby overnight public information is disseminated into opening and subsequent prices, and by filtering out the exogenous price effects, to more precisely determine the remaining endogeneous price effects. Applying the research of Ball and Bowers (1988), Eun and Shim (1989), Becker, Finnerty and Gupta (1990), Hamao, Masulis and Ng (1990)7 the previous day's lagged return on the DJ65 Stock Composite Index8 was determined as the appropriate overnight information set. An intervention model and price transfer identity was first specified as:

6 The input series (DJ65) was tested for a unit root using the Dickey Fuller test outlined in footnote 3. The test statistic was -4.70 against a critical value of -2.57. The hypothesis of a unit root was rejected and the series accepted as stationary.

7 US equity returns have the most influence and leads other domestic stock markets, and returns on the Australian market lag the US market by one day.

8 The DJ65 was used instead of a more broadly based index because the smaller index was deemed to contain a greater proportion of macroeconomic information rather than US firm specific information contained in, say, the S&P 500 index.
\[
\frac{\gamma}{1 - \alpha B} \text{ DJ65} \quad (4.4)
\]

where

- DJ65 is the previous day's log relative return on the DJ65 Composite Index
- \( \gamma \) is the coefficient of impact of the DJ65 return on opening Australian prices
- \((1-\alpha B)^{-1}\) is a polynomial in lag B.

Noting that:

\[(1-\alpha B)^{-1} = 1 + \alpha B + \alpha^2 B^2 + \alpha^3 B^3 \ldots \]

and constraining \(|\alpha| < 1\), then identity (4.4) can also be expressed as:

\[
\gamma \sum_{k=0}^{\infty} (\alpha B)^k \text{ DJ65} \quad (4.5)
\]

Equation (4.5) allows the price impact of information to be described in a number of ways. If the previous day's return on the DJ65 has some information value at the opening of trading on the Australian market then \( \gamma \) should be positive and significant. In addition if \( \alpha \) is equal to zero, then the overnight information from the US market only impacts on opening price returns and is represented by \( \gamma \text{ DJ}_t \) (Model 1). This scenario is more likely to occur under complete and perfect market assumptions where information is instantaneously impounded into security prices at the earliest opportunity and there is no leakage or transfer across into later prices.

Setting \( \gamma \text{ DJ65} \) equal to \( I_t \), then if \( \alpha \) is positive and less than one \((0 < \alpha < 1)\) the information impact from the US market is not completely impounded into returns at market opening and has a transfer effect in the following form

\[
\left[ 1 + \alpha B + \alpha^2 B^2 + \ldots + \alpha^k B^k \right] I_t \quad (4.6)
\]

That is, an exponential decay transfer function whose rate of transfer into prices is determined by the \( \alpha \) coefficient (Model 2). This scenario is likely to occur under
conditions of less than perfect information transfer when markets take some time to fully reflect information shocks into prices.

Finally, if there is price over-reaction to information shocks then the transfer into intraday prices can be modelled according to the following lag function (Model 3):

$$\left[ \frac{1 + \alpha B}{1 + \beta B} \right] I_t$$

(4.7)

constraining $|\beta| < 1$ and rearranging (6), then:

$$= \left[ (1 + \alpha B) \sum_{k=0}^{\infty} (-1)^k (\beta B)^k \right] I_t$$

$$\Rightarrow \left[ \sum_{k=0}^{\infty} (-1)^k \beta^k B^k + \alpha \sum_{k=0}^{\infty} (-1)^k \beta^k B^k + 1 \right] I_t$$

$$\Rightarrow \left[ 1 + \sum_{k=1}^{\infty} (-1)^{k+1} \beta^k B^k + \alpha \sum_{k=1}^{\infty} (-1)^{k+1} \beta^{k-1} B^k \right] I_t$$

$$\Rightarrow \left[ 1 + \left[ \sum_{k=1}^{\infty} \left( (-1)^{k+1} \beta^k + \alpha(-1)^{k+1} \beta^{k-1} B^k \right) \right] I_t \right]$$

(4.8)

From equation (4.8) the initial impact ($I_t$) from the US market during the following morning trading in the Australian market would evolve such that the cumulative shock at 1100 would be:

$$\left[ 1 + (\alpha - \beta)B^1 + (\beta^2 - \alpha \beta)B^2 + (\alpha \beta^2 - \beta^3)B^3 + (\beta^4 - \alpha \beta^3)B^4 \right] I_t$$

(4.9)
Note that if the coefficient on $\beta$ is greater than $\alpha$ then the combined effect will oscillate between a negative and positive impact on the lagged value of $I_t$. Figure 1 plots the processes that the three hypothetical price impact models might induce on AOI returns after a positive overnight return on the US market.

Figure 4.2 Theoretical models of the impact of information on opening AOI returns. Models 1 and 2 both assume an intervention and transfer function of the form $[(\gamma)/(1 - \alpha B)]\text{DJ65}$. Model 1 assumes: $\gamma=0.4$, $\alpha=0$, and $\text{DJ65}=1\%$. Model 2 assumes: $\gamma=0.4$, $\alpha=0.3$, and $\text{DJ65}=1\%$. Model 3 assumes an intervention and transfer function of the form $[(\gamma + \alpha B)/(1 + \beta B)]\text{DJ65}$ where $\gamma=0.4$, $\alpha=0.2$, $\beta=0.4$ and $\text{DJ65}=1\%$. 
4.4.3 Model Formulation, Estimation and Checking

Combining the components of the model discussed above the following model was applied to the AOI and SPI return series ($\eta_t$):

$$\eta_t = \sum_{i=1}^{q} \Psi_i \eta_{t-i} + \sum_{j=1}^{n} \nu_j (B) X_{j} + \nu(B) I_t + \epsilon_t$$  (4.10)

where

- $\sum_{i=1}^{q} \Psi_i \eta_{t-i}$ represents the autoregressive time series effects from previous returns;
- $\sum_{j=1}^{n} \nu_j (B) X_{j}$ represents both significant return spikes in intraday trading returns and $\nu_j(B)$ the transfer from the return spike;
- $\nu(B) I_t$ represents the impact of an input variable ($I_t$) on $\eta_t$; and
- $\epsilon_t$ is the residual term.

In the case of spikes in the intraday trading returns, if for example there is a return spike at 1015 which affects later returns, it is represented in (4.10) as $[\delta_1/(1-\theta B)] X_t$, where

$$X_{1t} = 1, \ t = 1015, \ otherwise = 0.$$  

Alternatively, if there is a return spike at a particular time, say 1100, which does not affect later returns, this would be accounted for in (4.10) as $\delta_2 X_t$, where

$$X_{2t} = 1, \ t = 1100, \ otherwise = 0.$$  

The previous day’s return on the DJ65 is an input variable into equation (4.10) as it is hypothesised to impact on $\eta_t$. This is accounted for through the intervention ($I_t = DJ65_t$) which is zero for $t < 1000$ in the stock market (0950 in futures) and $\nu(B)$ taking some
functional form to be identified from the data for \( t \geq 1000 \) in the stock market (0950 in futures).

Following Box-Jenkins model formulation (identification\(^9\)) techniques both for autoregressive integrated moving average (ARIMA) and transfer function models, and introducing appropriate interventions to account for significant spikes or jumps in the return series data, an appropriate model was determined. The unknown parameters in the model were estimated simultaneously by maximum likelihood via nonlinear least squares.\(^{10}\)

A number of competing models were considered and estimated. For example, a trend variable was initially fitted to test for any monthly or seasonal trends (eg. as the futures contract matured), but no significant trend was detected. The adequacy of the fitted model was determined by checking the statistical significance of the coefficients and performing diagnostic checks on the residuals in order to confirm that they satisfied the assumed conditions (Box-Ljung test). Competing models were compared using the Schwartz Bayesian Criterion (SBC),\(^{11}\) with the final model selected taking the form:

\[
\eta_t = \psi_1 \eta_{t-1} + \psi_2 \eta_{t-2} + \psi_3 \eta_{t-5} + \psi_4 \eta_{t-10} + \psi_5 \eta_{t-20} + \delta_1 X_{1t} + \\
[\delta_2/(1 - \phi B)] X_{2t} + [\delta_3/(1 - \omega B)] X_{3t} + \delta_4 X_{4t} + [(\gamma + \alpha B)/(1 + \beta B)] DJ65
\]

where the \( \eta_{t-j} \), \( j = 1, 2, 5, 10, 20 \) represent the autoregressive components of the model:

\[
X_{1t} = 1, \ t = 1000, \ otherwise = 0.
\]
\[
X_{2t} = 1, \ t = 1015, \ otherwise = 0.
\]

\(^9\) The identification procedure is fully outlined in Appendix 4.1. See also Poskitt (1989).

\(^{10}\) The statistical procedure used was the SAS ARIMA package [SAS/ETS Users Guide, Version 6, First Edition, Chapter 7, 1990].

\(^{11}\) Alternative Information Criteria such as the Akaike Information Criteria (AIC) could also have been applied. However, the Schwartz Bayesian Criterion (SBC) which imposes a stiffer penalty on additional regressors by adding regressors until the estimated gain from reduced bias offsets the estimated loss of power (and hence leads to a more parsimonious model compared to the AIC) was preferred. [see Schwartz (1978)].
\[ X_{3t} = 1, \ t = 1430, \ \text{otherwise} = 0. \]
\[ X_{4t} = 1, \ t = 1600, \ \text{otherwise} = 0. \]

DJ65 represents the previous day's return on the Dow Jones Composite Stock Index and \( \psi_j \) (\( j = 1, \ldots, 5 \)), \( \delta_j \) (\( j = 1, \ldots, 4 \)), \( \phi \), \( \omega \), \( \gamma \), \( \alpha \), and \( \beta \) are parameters to be estimated. The estimated coefficients, together with their associated t-ratios, are listed in Table 4.3. This estimated model implies the following:

(i) The first order autoregressive coefficient is high and positive, followed by slight negative autocorrelation at lag two, with some positive autocorrelation at longer lags. In economic terms, the positive first order autocorrelation might be explained by the lagged effects from thin trading and the positive autocorrelation at lag twenty the effect from the previous day's trading at the same time.

(ii) There are fixed positive returns at the opening and closing of trading (1000 and 1600) and negative spikes at 1015 and 1430. The negative spike at 1015 almost exactly reverses the positive opening spike. These spikes still remain after controlling for thin trading and overnight information impacts.

(iii) At 1015 and 1430 the transfer models signify that these spikes have a 'pulse' transfer which affects returns at the next lag. For example, the previously identified spike at 1030 (Table 4.2), is explained by the transferring of 52.8\% of the 1015 price returns into the 1030 returns; with a similar impact flowing from returns at 1430 into returns at 1445.

(iii) The intervention model reveals that the previous day's return on the US market (DJ65\( _t \)) as a large impact at the opening of trading. The coefficient (\( \gamma \)) of 0.337 signifies that about one-third of the return on the DJ65 is impounded into opening price returns in the Australian stock market. Further, the impulse coefficients (\( \alpha, \beta \)) reveal that about 14\% (0.203 - 0.340) of the initial impact (\( \gamma \) DJ65) is negatively transferred into the return...
at 1015. One interpretation of this return behaviour is that there is overreaction, followed
by a correction, in response to overnight information from the US market.\(^\text{12}\)

**Table 4.3**

*Results: Maximum Likelihood Estimation of AOI Intraday Returns*

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>T-Ratio</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\psi_1)</td>
<td>0.23249</td>
<td>16.41</td>
<td>Return lag 1 period</td>
</tr>
<tr>
<td>(\psi_2)</td>
<td>-0.03623</td>
<td>-2.56</td>
<td>Return lag 2 periods</td>
</tr>
<tr>
<td>(\psi_3)</td>
<td>0.03947</td>
<td>2.86</td>
<td>Return lag 5 periods</td>
</tr>
<tr>
<td>(\psi_4)</td>
<td>0.03794</td>
<td>3.74</td>
<td>Return lag 10 periods</td>
</tr>
<tr>
<td>(\psi_5)</td>
<td>0.03428</td>
<td>2.48</td>
<td>Return lag 20 periods</td>
</tr>
<tr>
<td>(\delta_1)</td>
<td>0.02628</td>
<td>3.16</td>
<td>Fixed return 1000</td>
</tr>
<tr>
<td>(\gamma)</td>
<td>0.33734</td>
<td>28.47</td>
<td>US impact at opening</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>-0.20335</td>
<td>-6.59</td>
<td>US transfer numerator lag 1</td>
</tr>
<tr>
<td>(\beta)</td>
<td>-0.34039</td>
<td>-3.33</td>
<td>US transfer denominator lag 1</td>
</tr>
<tr>
<td>(\delta_2)</td>
<td>-0.02687</td>
<td>-3.26</td>
<td>Fixed return 1015</td>
</tr>
<tr>
<td>(\phi)</td>
<td>0.52788</td>
<td>2.53</td>
<td>Pulse transfer denominator (\delta_{1015})</td>
</tr>
<tr>
<td>(\delta_3)</td>
<td>-0.01868</td>
<td>-2.33</td>
<td>Fixed return 1430</td>
</tr>
<tr>
<td>(\omega)</td>
<td>0.51415</td>
<td>1.67</td>
<td>Pulse transfer denominator (\delta_{1430})</td>
</tr>
<tr>
<td>(\delta_4)</td>
<td>0.03757</td>
<td>4.65</td>
<td>Fixed return 1600</td>
</tr>
</tbody>
</table>

**Residual Analysis**

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.001763</td>
</tr>
<tr>
<td>Variance</td>
<td>0.015103</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.5847</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>11.23</td>
</tr>
<tr>
<td>t for mean = 0</td>
<td>1.07</td>
</tr>
<tr>
<td>Schwart BC</td>
<td>-6639.54</td>
</tr>
<tr>
<td>Number of residuals</td>
<td>4979</td>
</tr>
</tbody>
</table>

**Autocorrelation Check of Residuals**

<table>
<thead>
<tr>
<th>To lag</th>
<th>Chi Square</th>
<th>DF</th>
<th>Prob</th>
<th>Autocorrelations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Auto Correlations</td>
</tr>
<tr>
<td>6</td>
<td>2.07</td>
<td>1</td>
<td>0.150</td>
<td>-0.000</td>
</tr>
<tr>
<td>12</td>
<td>10.96</td>
<td>7</td>
<td>0.140</td>
<td>0.015</td>
</tr>
<tr>
<td>18</td>
<td>16.85</td>
<td>13</td>
<td>0.206</td>
<td>0.028</td>
</tr>
<tr>
<td>24</td>
<td>22.55</td>
<td>19</td>
<td>0.258</td>
<td>0.025</td>
</tr>
<tr>
<td>30</td>
<td>31.11</td>
<td>25</td>
<td>0.186</td>
<td>-0.003</td>
</tr>
<tr>
<td>36</td>
<td>39.03</td>
<td>31</td>
<td>0.152</td>
<td>0.039</td>
</tr>
<tr>
<td>42</td>
<td>46.24</td>
<td>37</td>
<td>0.142</td>
<td>-0.007</td>
</tr>
</tbody>
</table>

\(^{12}\) One examiner suggested that the random opening procedure on SEATS would mean that only about
half the stocks with ASC codes A-C will have opened at 1000 and that 1015 was the appropriate
time to assess the ability of the stock market to price overnight information. This problem was
addressed by re-estimating equation 4.10 assuming that 1015 was the opening price. The results
indicated a negative relationship between opening returns and overnight US returns (-0.10053, t-stat
-6.20) which is contrary to economic expectations. A possible explanation is that ASC codes A-C
incorporate a number of the largest price leader firms in Australia and the price at 1000 sets the tone
for the rest of the market. Further, the 1015 spike was fixed and significant (0.000237, t-stat 2.40)
but there was no evidence of over-reaction at 1030.

\(^{13}\) The Chi Square values used in the test for lack of fit are computed using the formula:

\[
\chi^2_m = n(n+2) \sum_{k=1}^{m} \frac{a^2_k}{(n-k)} \text{ where } t = \sum_{k=1}^{n-k} a_t a_{t+k} / \sum_{k=1}^{n} a_t^2 \text{ and the } a_t \text{ are the residuals [Ljung and Box (1978)]}
\]
Table 4.3 also exhibits summary statistics relating to the residual analysis which determines the goodness of fit of the model. An examination of the residuals from the model showed that they were well behaved. The mean was not significantly different from zero, there was no skewness and stem and leaf plots indicated that the distribution was approximately normal. There was some positive excess kurtosis clustered around the lunchtime residuals and this suggests that there are some fundamental factors which affect trading in the stock market at that time. The Ljung-Box chi-square statistic is also reported along with the autocorrelation of the lagged residuals as a test for lack of fit. This statistic shows that there is no significant autocorrelation structure in the residuals and the model is acceptable. Finally, the transfer function model significantly improved the fit obtained from only the autoregressive and fixed time of the day model.\textsuperscript{14} The Schwartz's Bayesian Criterion (SBC) improved from -6083.55 to -6639.54 and the residual variance of the final equation was reduced by 13.5\%.

**SPI Series**

The general model outlined in equation (4.10) was also applied to the SPI return series ($\eta_{1t}$) and the best fitting model determined as:

$$
\eta_{1t} = \psi_1 \eta_{1t-1} + \psi_2 \eta_{1t-4} + \psi_3 \eta_{1t-8} + \psi_4 \eta_{1t-20} + \delta_1 X_{1t} + \delta_2 X_{2t} + \delta_3 X_{3t} + \left[ (\gamma)/(1 - \beta B^2) \right] DJ_{65}
$$

where $\eta_{1t-j}$, $j = 1, 4, 8, 20$ represents the autoregressive components of the model, and the following dummy variables represent the significant intraday return spikes:

$X_{1t} = 1$, $t = 1000$, otherwise $= 0$.  
$X_{2t} = 1$, $t = 1015$, otherwise $= 0$. 

\textsuperscript{14} There are three approaches to modelling return series: (1) the classical or conditional mean approach, (2) ARCH, GARCH or EGARCH models, and (3) a combination of the above two. The classical approach was used here which requires the effectiveness of the modelling procedure to be checked by diagnostic analysis of the residuals. These checks have shown that the autoregressive parameters, and transfer, pulse and dummy variables have adequately modelled the return behaviour.
\[ X_{3t} = 1, \ t = 1430, \ \text{otherwise} = 0. \]

Similarly for the AOI series, the DJ65 represents the previous day’s return on the Dow Jones Composite Stock Index and \( \psi_j \ (j = 1, \ldots, 4) \), \( \delta_j \ (j = 1, \ldots, 3) \), \( \gamma \), and \( \beta \) are parameters to be estimated. The estimated coefficients, their associated t-ratios, and the residual analysis are listed in Table 4.4 and imply the following:

(i) In contrast to the AOI, the SPI return series had low and negative first order autocorrelation with weak positive autocorrelation at higher lags. This result is consistent with previous research in the US, which has been explained by the greater speed of adjustment of futures markets to information and the infrequent trading in the component stocks of stock indices which induces a price reaction lag.

(ii) A positive fixed spike in SPI futures returns is observed at 1000 with negative spikes at 1015 and 1430. After the filtering process provided by the model, the spike at 1000 has only changed slightly from the unconditional statistical analysis. In contrast to the AOI returns, there were no statistically significant return spikes at the opening and closing of the futures market (at 0950 and 1610) when trading was suspended in the stock market, and no transfer effects from the intraday price spikes into neighbourly prices.

(iii) The coefficient on the US intervention (\( \gamma \)) was higher for the SPI compared to the impact on the AOI series (0.562 vs. 0.337). After taking this impact into account there is no significant fixed time of the day effect in the futures market at opening - the initially observed return spike at 0950 of 0.00033 (see Table 4.2) has been explained by the overnight information from the US market. What is more interesting is that the negative overreaction to the US market occurs at the second lag in the futures market\(^{15} \) at 1015 and not at the first lag as is the case in the stock market. It appears that the futures market has three pieces of information to contend with and it does so in a linear fashion. First, the arrival of overnight information at 0950, next the opening of the stock market at 1000, and then the overreaction at 1015.

\(^{15} \) The coefficients of the intervention transfer function are \([0.562/ (1 - 0.125B^2)] \) DJ65\(_{t-1}\).
The residual analysis from SPI transfer function time series model showed that the model was acceptable. The Ljung-Box chi-square statistic shows no autocorrelation structure in the residuals which approximated a normal distribution around zero. Further, the addition of the overnight information intervention to the autoregressive and fixed time of the day model improved the SBC from -1644.02 to -2485.76 and reduced the residual variance by 20%.

### Table 4.4

**Results: Maximum Likelihood Estimation of SPI Intraday Returns**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>T Ratio</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Psi_1$</td>
<td>-0.04323</td>
<td>-3.20</td>
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</tr>
<tr>
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<td>Return lag 4 period</td>
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</tr>
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<tr>
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<tr>
<td>$\delta_3$</td>
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**Residual Analysis**

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<tr>
<td>Variance</td>
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<td>2779</td>
</tr>
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<td>Schwartz IC</td>
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<tr>
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</table>

**Autocorrelation Check of Residuals**

<table>
<thead>
<tr>
<th>To Lag</th>
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<th>DF</th>
<th>Prob</th>
<th>Autocorrelations</th>
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</thead>
<tbody>
<tr>
<td>6</td>
<td>4.59</td>
<td>2</td>
<td>0.101</td>
<td>-0.001 -0.018 -0.002 -0.001 -0.005 -0.010 0.017</td>
</tr>
<tr>
<td>12</td>
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<td>8</td>
<td>0.421</td>
<td>-0.015 -0.001 -0.003 -0.005 -0.010 0.012 -0.004</td>
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<td>12.74</td>
<td>14</td>
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<td>0.003 0.019 -0.014 0.010 0.012 0.010 -0.004</td>
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<tr>
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<td>0.000 0.002 0.023 -0.005 -0.024 -0.015</td>
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<td>0.931</td>
<td>0.003 -0.003 -0.004 -0.018 -0.003 0.003</td>
</tr>
</tbody>
</table>

Figure 3, Panels A and B, provides a visual comparison of the return spikes before and after adjusting for the impact of overnight information and various trading microstructures using the transfer function time series model. This plot shows that the modelling process has partly explained the intraday price return spikes but significant return spikes still remain.
Figure 4.3 Intraday return spikes before and after filtering using transfer function time series models.

Unconditional return spikes are the raw returns reported as significant in Table 4.2 and conditional return spikes are those reported as significant in Tables 4.3 and 4.4.
4.5 SUMMARY AND DISCUSSION OF RESULTS

The above analyses incorporated a number of potential explanations for the observed intraday price return spikes on the Australian stock market. Thin trading in the component shares of the AOI index may mean that the opening spike is simply a lagged adjustment to large closing returns from the previous day. The large and positive first-order autoregressive parameter (0.232) confirms the perception that the Australian sharemarket suffers from a nonsynchronous trading effect. The overnight information contained in the previous day's return on the DJ65 Composite Index has a significant positive impact on the 1000 overnight price return in the Australian stock market. However, using 1015 as the opening return the coefficient of the impact from the US was negative. This is possibly caused by the fact that a number of large firms in Australia are actually opened at 1000.

After filtering out these effects it was determined that approximately 37% of the opening price spike at 1000 in the AOI is explained by these factors. The unconditional opening return fell from 0.000428 to 0.000263 but remains statistically significant. One plausible explanation for this result is that the remaining opening spike is a consequence of other information, both public and private, that has not been captured by the model. The use of the SPI futures as a control is a secondary source to observe the effects of the overnight information impact. First, the overnight US return has a higher impact on opening futures prices ($\gamma = 0.562$) compared to opening stock prices ($\gamma = 0.337$). The smaller impact in the stock market is probably related to the random opening procedure employed in the stock market which means that not all stocks are open for trading at 1000. Secondly, there is a differential impact between the markets. The opening spike in the futures at 0950 is due solely to the external US market, but the large 1000 spike (0.000426) remains. If there are other potential sources of information, then the futures market does not appear to be incorporating that information into account at opening, and this appears to nullify this information argument. It appears that the futures market first reacts to the overnight US information and then awaits developments in the stock market before, then again, reacting to the information set contained in those changes in stock prices. This
explanation, however, is at odds with a number of previous studies which argued that futures markets are less costly and more liquid to utilise than equity markets and, therefore, futures markets are likely to be more dominant in revealing macro information. This implies that if traders prefer futures contracts rather than component stocks, an asymmetric lead-lag relation should hold between the returns of futures contracts and all stocks in a broad based index [Stoll and Whaley (1990a), Chan, Chan and Karolyi (1991) and others]. Certainly, the futures market has a greater price change reaction to overnight information at 950 and 1000. One explanation could be that the price setting mechanism and screen trading in equities, compared to the open outcry system in futures, is an effective mechanism in inhibiting overreaction.

For this to be a plausible explanation there should be no subsequent price reversal at 1015 or there should be a restrained transfer of information into neighbourly prices. The statistical evidence does not support this contention with the impact of US returns being transferred into 1015 equity prices in a manner consistent with a short term overreaction hypothesis. Both transfer numerator ($\alpha$) and denominator ($\beta$) are statistical significant at lag1 and the net effect at 1015 (-0.137) indicates that 13.7% of the initial price impact from the US return is reversed at this time. However, the reversal of the impact from the overnight information does not fully explain the negative spike at 1015 and it still remains. Interestingly, after filtering out the overnight effects, the 1000 and 1015 returns in the equity market are approximately equal but opposite in sign (0.000263, -0.000269). For the futures market, there is no statistical evidence of any transfer into 1000 prices from the US return, with the overreaction waiting a further fifteen minutes in order to occur contemporaneously with the AOI at 1015. Similar to the AOI, about 12.5% of the initial impact from the US is reversed at 1015 with a remaining negative return spike of -0.000282. These observations support a short term overreaction hypothesis in both markets [DeBondt and Thaler (1989)] and the results in the futures market suggest that traders may have short term horizons and tend to focus on one information source at a time [Froot, Scharfstein and Stein (1992)].
Some other features are also worth noting. The autoregressive process was strongly positive for the AOI series and weakly negative for the SPI series. This confirms the prior perception that the Australian equity market suffers from a nonsynchronous trading effect. There is no evidence of any price transfer into subsequent prices, at or around the negative fixed time of the day effects at 1015 and 1430, in the SPI futures. In contrast, the significant coefficients on the evolution functions at these times for the AOI equity market suggests a slower mean reversion factor compared to futures prices. Finally, the closing price spike in the AOI is positive and significant, but this is not the case for the SPI.

4.6 CONCLUSION

This chapter identifies and filters out the dynamic effects of the previous day's return on the DJ 65 Stock Composite Index, as a specified and publicly observable overnight information set, on the opening and subsequent AOI and SPI price returns. This is achieved by including the effects of an overnight intervention in transfer function time series models. It was determined that the information from the overnight US stock market had a differential impact on the Australian stock and futures market. After filtering out the overnight information impacts a positive and significant price spike remained in both markets at 1000 followed by a price reversal at 1015. Further analysis of both markets suggests that the price spikes at the opening of the Australian market may not be wholly related to overnight information. Other possible explanations, such as different trading mechanisms, do not provide a satisfactory explanation.

Overall, it appears that the uncertainty that participants face at the beginning of a trading session may induce a number of subtle market reactions (both rational and irrational), in the price return series in markets with different micro-structures and trading clientele. Price returns can be considered to be the market consensus on the impact of information on prices, whilst price volatility can be considered as the degree to which traders disagree about the meaning of information. Further analysis is undertaken in the next chapter to examine the intraday patterns in futures trading volume and the additional impact of raw trading volume and surprises in trading volume on price returns.
Appendix 4.1

Identification Procedure

The identification of the appropriate transfer function and the noise model applied is described by Box and Jenkins (1976, Ch. 11), and revolves around the cross correlation function (CCF) between $\eta$ and $I$. The procedure involves the technique of prewhitening the input ($I$) and output series ($\eta$) as follows:

Step 1: Prewhiten the input series by first obtaining the ARMA model

$$\phi_x(B) X_t = \theta_x(B) \alpha_t$$

and then generate the white noise series $\alpha_t$

$$\alpha_t = \theta_x^{-1}(B) \phi_x(B) x_t$$

Step 2: Transform the output series using the same filter by generating the series

$$\beta_t = \theta_x^{-1}(B) \phi_x(B) y_t$$

Step 3: Estimate

$$\hat{\rho}_{k} = \frac{S_{\beta}}{S_{\alpha}} \rho_{\alpha\beta}(k)$$

where $S_{\alpha}$ and $S_{\beta}$ are the estimated standard deviations of the $\alpha_t$ and $\beta_t$ series and $\rho_{\alpha\beta}(k)$ is the sample cross correlation function between $\alpha_t$ and $\beta_t$ at lag $k$.

Step 4: Obtain preliminary estimates of $\hat{\alpha}$ and $\hat{\beta}$ by estimating

$$\eta_t = \hat{\eta}(B) I_t + N_t$$

where $\hat{\eta}(B)$ is equal to $\frac{\hat{\omega}(B) B^\beta}{\hat{\delta}(B)}$ as defined in equation (4.2) and with $N_t$ assumed to be a sequence of uncorrelated random observations from a fixed distribution which is normal (often described as white noise).

Step 5: Generate the endogeneous series

$$\hat{N}_t = \eta_t - \hat{\eta}(B) I_t = \eta_t - \hat{\delta}^{-1}(B) \hat{\omega}(B) I_t$$

and specify an appropriate model to describe this series. The identification of the endogeneous model $N_t$ is usually carried by applying standard Box-Jenkins (1976) methods of identification-estimation-diagnostic checking.
CHAPTER FIVE

INTRADAY TRADING VOLUME

5.1 INTRODUCTION

The behaviour of trading volume and the interaction between price changes and volume is a topic which has attracted some considerable interest among academics and professional traders. There are a number of reasons why trading volume is important in the study of financial markets. Karpoff (1987) reviews the relation between price changes and trading volume and documents four reasons. First, the relation provides insights into the structure of financial markets and the rate of information flow and dissemination. Second, if price changes and volume are jointly determined the price changes can be interpreted as the market evaluation of new information, whilst the corresponding volume can be considered an indication of the extent to which investors disagree about the meaning of information. Third, the price-volume relation may shed light on the distribution of speculative prices which appear leptokurtic over fixed trading intervals. Fourth, price-volume relations may have significant implications for futures markets which in turn may spillover into the underlying cash market.

The role of futures market trading has been the focus of substantial recent attention in the US, including studies by the New York Stock Exchange, the Commodity Futures Trading Commission, the Securities and Exchange Commission, the United States General Accounting Office and a Presidential Task Force. In Australia the Australian Securities Commission released a report on over the counter derivative trading in May
1994. One focus of these reports has been the impact of derivative trading volume on price setting in futures and cash markets.

This chapter has a number of objectives. The first is to provide a description of the intraday pattern of trading volume in the Australian SPI futures market. One of the observations from chapter four was that the end of day volatility was more subdued in Australia. Given the theoretical and empirical research which suggests a strong relation between price changes and trading volume [Karpoff (1987, Table 4, pp 113)] it is of interest to document the pattern of trading volume in Australia.

Previous empirical research has used raw volume or a measure of 'abnormal' volume. If abnormal changes in trading volume are a better explanation of price movements, then the specification of a trading volume expectations model is required. There is, however, no widely accepted model that has been applied for generating ex ante volume expectations.¹ A second objective is to derive an expectations model of trading volume which can be applied to intraday trading volume data. This is achieved by fitting polynomial functions to intraday volumes and by taking into account known factors which affect trading volume; specifically the Monday effect, and bull and bear days.

Once the above measure of abnormal trading volume is derived then, together with a random walk expectations volume model, trading volume is tested for its association with SPI and AOI price changes. This is an important question as it addresses the problem of how much of the price change can be attributed to information arrival or market structure, rather than simply to trading activity. Further questions about whether trading volume leads price changes or vice versa are also addressed. A brief background to the research problems examined is now presented.

5.2 BACKGROUND

Trading volume in security markets may be affected by a number of factors which include:

(i) heterogeneous expectations;
(ii) information asymmetry;
(iii) risk;
(iv) liquidity trading;
(v) market microstructure; and
(vi) speculation.

5.2.1 Heterogeneous Expectations

Trading volume is often taken as reflecting the differential impact of information on the expectations of individual traders. Price changes represent the aggregate consensus evaluation of information whilst changes in the corresponding trading volume are considered to be a proxy for the extent to which traders disagree (or have heterogeneous expectations) about the meaning of information.

There are a number of hypotheses which investigate the degree to which traders disagree about the meaning of information, the impact on trading volume and the association between price and volume. This relationship is also perceived to be of some importance in the market place. For example, Tauchen and Pitts (1983) proposed a mixture of distributions hypothesis (MDH) whereby price changes and trading volume are simultaneously determined. The MDH states that the correlation between price changes and trading volume should be positive because of a joint dependence on the amount of information impacting the market, and hence to each other. This means that trading volume and prices should change contemporaneously because they both react similarly to the arrival of unexpected information.

On the other hand, the sequential information model hypothesis (SIH) proposes that there are intermediate equilibrium in trading volume prior to the final complete information equilibrium [Copeland (1976), Morse (1981), Jennings, Starks and Fellingham (1981),...
Jennings and Barry (1983)]. This implies that traders are not instantaneously informed and cannot perfectly infer the presence of informed trading. Information is assumed to reach traders in sequence; that is each trader trades on the information before it reaches the next trader. Traders are classified as 'pessimistic' or 'optimistic' and the sequence of pessimistic or optimistic trades determines volume.

Epps (1975) has also constructed a heterogeneous model that implies that trading volume on price upticks is greater than volume on downticks. His model relies on behavioural distinctions between two types of investors: 'bulls' and 'bears'. Bulls are more optimistic about the value of the security at the end of the trading period and they react only to positive information. Conversely, the pessimistic bears react only to negative information. In this market the transaction demand curve consists of bull traders and bears comprise the supply curve. Epps demonstrates that the demand curve is steeper than the supply curve and the ratio of trading volume to a positive price change is greater.

Some of these heterogeneous theoretical models are reflected in market folklore such as: '... it takes volume to make prices move' and '... volume is heavy in bull markets and light in bear markets', and reflect the perceived importance of the relationship between volume and prices. For technical analysts, who favour the psychological approach, the price-volume relationship is used to extract the current 'mood' of the market. For fundamental analysts, if there is an economic relation between demand and supply, there may be lead-lag relationships which can be used to econometrically predict future movements.

5.2.2 Information Asymmetry

Information asymmetry can cause prices to deviate from previous prices and create trading opportunities [Morse (1980)]. Information asymmetry also plays a joint role in the basic assumptions of the sequential information arrival hypothesis (SIH) and the private information trading models [Admati and Pfleiderer (1988)]. Trading volume in these models is created with a lag in reaction to the release of information through the trading of
other traders. Furthermore, Fabozzi, Ma and Linkstey (1988) proposed that information asymmetry leads to overreaction in prices with trading volume following price changes with a lag.

5.2.3 Risk

Trading volume has also been related to shifts in risk clientele or risk preferences [Verrecchia (1981), Hankannson, Runkel and Ohlson (1984)]. The clustering of trading volume around the open and close of trading may be due to the desire of some traders to exchange the risk of holding positions overnight and may not be related to information effects.

Gerety and Mulherin (1992) argued that investors may differ in their willingness to hold positions overnight and this may explain the U-shaped pattern in trading volume. Day traders who do not trade on information are particularly vulnerable to averse private information which becomes public overnight and on weekends. This risk is accentuated in futures markets where trading is undertaken on margin deposit. If day traders are very active in futures then this hypothesis predicts a stronger U-shaped pattern in intraday futures trading volume. Conversely if futures markets are ex ante information predictive, trading volume at the close may be related to expected overnight price movements.

5.2.4 Liquidity

Liquidity considerations, which may or may not necessarily be related to the arrival of information, are also important in security markets. For example, major financial institutions trade for portfolio rebalancing reasons whenever internal policy changes or the index constituents change.

Futures markets offer traders a liquid, low cost and levered market in which to trade on private or new information. In a perfect market there should be simultaneity in trading activity between the markets but these institutional features in the futures market
potentially make futures trading a more liquid market for information traders. A number of theoretical studies have differentiated between the types of information that flow to cash stock and index futures markets. For example, Kumar and Seppi (1989), Chan (1990), and Subrahmanyam (1991) showed that fixed costs of trading, budget constraints, and different expected profits caused traders in futures markets to collect more marketwide information and traders in cash markets to collect more firm specific information. One impact of higher liquidity in futures might be that trading volume in SPI futures leads prices in the comparably thin AOI stock market.

5.2.5 Market Structure

The structure of the market may impact on trading volume. The use of circuit breakers, the pattern of predictable market closings, the availability of overnight trading, and trading and price setting mechanisms have implications for trading volume. For example, in futures markets the structural feature of regular contract maturity induces trading volume in order to rollover the contract into the next maturity or by novating arbitrage maturity. Thus while the rate of flow of information may be random over the life of a futures contract, trading volume may be contract time specific.

Ma, Peterson, and Kao (1990) researched the effect of the addition of an evening session, in April 1987, on the trading patterns in the regular daily session. Among other things, the results indicated that 'the last daytime hour shows a marked decline in volume relative to volume in the rest of the day after evening trading commenced' [Ma, Peterson, and Kao (1990, p. 12)]. In Australia, overnight trading occurred on the futures market (SYCOM) from 1640 to 04002 the following morning and might have a dampening effect on trading volume at the end of the floor trading day.

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2 Trading hours were extended to 0600 on 10 January 1994
5.2.6 Speculation

Rutledge (1986) proposed that variations in futures trading volume are a surrogate for variations in price speculation. If, for example, transactions involving hedgers comprise only a small proportion of trading in futures markets then price changes may affect the volume of trading in futures contracts. If most trading in futures is speculative in nature then interval-to-interval variations in trading volume may be a proxy for interval-to-interval variations in speculative activity. The trading activities of speculators may be a stabilising or destabilising factor on futures prices and may even spillover into the underlying stock market.

5.2.7 Other Considerations

There are some other stylised observations on trading volume that are worth noting. Trading volume on Mondays is consistently lower than other days of the week [Jain and Joh (1988)]. Foster and Viswanathan (1993) contend that this is only true for actively traded markets because the lack of public information released on weekends reduces the possibility for discretionary liquidity traders and private information traders to 'cluster'. Unexpected trading volume has a greater association with price changes than measures of raw trading volume, and unexpected increases in trading volume have a relatively greater impact [Bessembinder and Seguin (1992,1993)]. Finally, there is some empirical evidence about the association between price changes and trading volume. Using a GARCH model Lamoureux and Lstrapes (1990) found that the persistence in the variance equation was greatly reduced with the addition of trading volume as a mixing variable. Hence there was a high association between price movements and trading volume. In contrast Locke and Sayers (1993) found significant variance persistence after controlling for trading volume. They suggested that price changes may be attributed to market information signals which were distinct from the usual information arrival proxies (such as volume). For example, favourable public announcements could cause a relatively large increase in price changes without a similar increase in trading volume and trading per se did not fully explain return changes or persistence in volatility.
Whilst there are several theoretical models for trading volume there is no general model which includes all of the above factors. Further, a major difficulty in determining the impact of trading volume is that there is no widely accepted model for generating ex ante trading volume expectations (e.g. like the Capital Asset Pricing Model). The following sections report the intraday behaviour of trading volume in the SPI futures market, develop an ex ante expectations trading volume model, and apply the expectations model to the SPI and AOI price returns.

5.3 DATA AND DESCRIPTIVE STATISTICS

The trading volume analysed was taken from the database outlined in chapter four. The SPI futures volume was used because trading volume in the futures has been associated with information arrival as well as speculative activity. Intraday trading volume was measured as the number of futures contracts traded over the preceding trading interval. For all intervals, except the opening and closing intervals, this interval was recorded in 15-minute periods. The opening interval from 0950 to 1000 and the closing interval from 1600 to 1610 was each 10-minutes in length. All together there were twenty intraday trading intervals. The mean SPI trading volumes by intraday periods for all days, bull versus bear days, and Mondays are reported in Table 5.1. Intraday statistics for trading volume over all days are plotted in Figure 5.1. They show a distinct U-shaped pattern for mean trading volume over the day. Trading volumes are highest at the start and end of the day consistent with the theory of Admati and Pfleiderer (1988) and the empirical observations of Jain and Joh (1988), Gerety and Mulherin (1992), Foster and Viswanathan (1993) (*in equities*) and Lauterbach and Monroe (1989) and Ekman (1992) (*in futures*).

The 10-minute closing period volume was the highest of the day and is about three times the average trading volume during the interior trading periods. The opening 10 minute period was the next highest traded period and was approximately twice as active as the trading volume of the interior periods. The lowest trading volume occurs either side of the lunchbreak from 1230 to 1400. An interesting result was an acceleration of trading
volume over the closing periods. This is in contrast with the empirical observations in the US where there is evidence that volume drops in intensity during the last 15 minutes. This result is in contradiction with predictions that the availability of overnight futures trading on SYCOM lessens the risk associated with holding open positions and therefore closing trading volume at the end of the day will be reduced. It is also interesting to note that whilst trading activity accelerates towards the close of trading at 1610 this is not associated with increased volatility (see chapter six). This observation is in contrast with theories which predict a contemporaneous volatility-volume relationship, and suggests that trading activity is induced by a number of different features over the day, such as public overnight information at opening or imminent closure. On the other hand, the distinct U-shaped pattern in returns observed in chapter four suggests a stronger relationship between returns and trading volume.

The standard deviation of intraday trading volume was also U-shaped and generally associated with the arrival of information in some form or another. It was highest at opening and closing, during the period 1130 to 1200 (associated with the release of macro information in Australia), and immediately after lunch. Figure 5.1 also show that raw intraday trading volume is positively skewed and leptokurtic and it is apparent that transformation of the data is required to achieve approximate normality. This is achieved by taking the natural logarithm of the raw volume and it appears that this transformation is successful (see Table 5.3). Thus, in any subsequent statistical modelling the transformed trading volume series is used.

Some empirical studies suggest that there is a contract maturity effect in futures trading volume [Martell and Trevino (1990), Bessembinder and Seguin (1993)]. There may not be uniform trading activity over the life of the futures contract. At the beginning of the life of the contract trading volumes may be small, but towards expiration there may be higher trading volumes as a consequence of traders rolling over current futures contracts into further contracts or because of higher volatilities towards expiration which might attract speculative trading. In order to examine the contract maturity trading volume
effect, the contract times to expiration were broken down into blocks of seven trading

days with one signifying the nearest time to expiration and nine the furthest. It was found

that period two (7-14 trading days prior to expiration) had the highest average daily

trading volume and period eight (49-56) the lowest. However, F-tests constructed from

ANOVA regressions showed that there were no significant differences at the 5% level

between average daily trading volumes over the life of the contract.

Table 5.1

Mean Volume By Intraday Trading Period

<table>
<thead>
<tr>
<th></th>
<th>All Days</th>
<th>Bear Days</th>
<th>Bull Days</th>
<th>Mondays</th>
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<td>67.86</td>
<td>66.37</td>
<td>69.07</td>
<td>54.42</td>
</tr>
<tr>
<td>1015</td>
<td>87.23</td>
<td>81.53</td>
<td>93.75</td>
<td>73.15</td>
</tr>
<tr>
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<td>81.64</td>
<td>79.61</td>
<td>84.01</td>
<td>68.75</td>
</tr>
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<td>47.26</td>
<td>44.85</td>
<td>40.94</td>
</tr>
<tr>
<td>1530</td>
<td>51.20</td>
<td>50.19</td>
<td>51.54</td>
<td>41.71</td>
</tr>
<tr>
<td>1545</td>
<td>52.74</td>
<td>54.80</td>
<td>48.53</td>
<td>43.75</td>
</tr>
<tr>
<td>1600</td>
<td>72.82</td>
<td>75.20</td>
<td>70.43</td>
<td>73.73</td>
</tr>
<tr>
<td>1610</td>
<td>95.76</td>
<td>97.67</td>
<td>94.06</td>
<td>100.50</td>
</tr>
</tbody>
</table>

Total 1161.13 1135.15 1181.48 1034.88

All trading periods are 15-minutes except the periods ending at 1000 and 1610 which are 10-minute

intervals.
Figure 5.1: Moments of Intraday SPI Trading Volume
Bull and Bear Days

The trading volume data was also decomposed between bull and bear days. Bull days were defined as days when the overnight return on the DJ65 was zero or positive and bear days when the overnight return was negative. The intraday trading volumes during these periods are reported in Table 5.1 which indicate that the pattern in trading volume is fairly robust to the price 'mood' of the market. The patterns are similarly U-shaped with the average daily trading volumes in bear market (1135.15) being below bull days (1181.48). During the first hour trading volumes in bear markets are some 5-10% lower than bull markets, but during the closing periods volumes in bear markets are slightly higher.

Monday Effect

A number of overseas studies have highlighted a Monday effect in trading volume. Trading volume is lowest on Mondays and highest in mid-week [Jain and Joh (1988), Foster and Viswanathan (1993)]. Brailsford (1994) and Aitken, Brown and Walter (1994) have observed lower Monday trading volumes in the AOI stock market in Australia. As reported in Table 5.1 this is also the case in SPI futures with the lower Monday trading volume occurring at the opening of trading after the long weekend nontrading halt. Average daily trading volume on Mondays is about 13% lower than the average for the remainder of the week. The early morning trading volumes are especially lower (up to 21%). The afternoon trading volumes are very similar in pattern and trading levels to the afternoon trading volumes for the remainder of the week.

5.4 INTRADAY TRADING VOLUME EXPECTATIONS MODELS

The existing theoretical analyses of the impact of trading volume on returns and volatility do not generally distinguish between anticipated and unanticipated components of trading volume. Given the emphasis on differentiating the effects of expected versus unexpected

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3 As the Australian market is a price follower the prediction of a bull and bear day is highly related to this factor.
components of variables across a wide spectrum of economic analysis, this chapter empirically determines and applies two expectations models to intraday trading volume. This is done in order to examine the proposition that surprises in trading volume (compared to raw trading volume) convey more information, and thus have a larger impact on prices.

The first model is a measure of the relative change in the log of trading volume (DTVR) using the following formula:

\[
DTVR = \log \left( \frac{Vol_{d_{it}}}{Vol_{d_{it-1}}} \right)
\]  

(5.1)

where \( Vol_{d_{it}} \) is the current intraday period observable trading volume and \( Vol_{d_{it-1}} \) is the trading volume which occurred during the same trading period on the previous trading day.\(^4\) The use of log volumes is roughly equal to the percentage deviation of volume from its expectation, where the expectation is equivalent to the trading volume observed over that same period on the previous trading day. This model has recently been applied by Bessembinder and Seguin (1992, 1993) to daily trading volume and is referred to as a random walk model. The slight modification\(^5\) is due to the fact that data used are intraday and the best estimate of trading volume is the trading volume last observed over an equivalent time of the day trading period.

Another variation of the random walk model is to use raw deviations in trading volume from the previous day's equivalent trading period. The problem with this measure is that, similar to raw trading volume, the distribution of raw deviations is decidedly non-normal. Table 5.3 reports descriptive statistics for the two random walk measures of unexpected trading volume and confirms that the distribution of the log relative measure approximates

\(^4\) For example, the expected trading volume for the \((i)\) th period, 1145 to 1200 on trading day \(t\), is the trading volume observed over the period 1145 to 1200 on trading day \(t-1\).

\(^5\) The observation of a 15-minute period trading volume on the previous day compared to total trading volume over the day.
a normal distribution. This proxy for ‘surprises’ in the previous day’s trading volume is therefore preferred for statistical modelling purposes.

The second model used was constructed by fitting polynomial functions to intraday trading volumes as an estimate of expected volume. The deviations from the fitted model were saved and used as a measure of unexpected trading volume. A number of different expectations models were specified in order to take account of the prior knowledge that the intraday trading patterns differ - specifically, Mondays and bull and bear days. Further, a variety of different functional forms were fitted to the raw trading volume data. Firstly, a number of polynomials were fitted to the data across the whole intraday trading period. Secondly, different polynomials were fitted separately for the morning and afternoon trading periods. It was found that the best explanatory models for the full data set involved fitting a polynomial of degree two (quadratic) to the morning trading data and a polynomial of degree three (cubic) to the afternoon data as follows:

\[ EV_M = \alpha + \beta (t_j - C)^2 \]  
\[ EV_A = \alpha + \beta (t_j - C)^2 + \gamma (t_j - C)^3 \]

where: \( EV_M \) and \( EV_A \) are the expected trading volumes in the morning and afternoon,

\( t_j \) (j = 1, ......., 20) are intraday times where 1000 is equal to 1, 1015 is equal to 2, up to 1610 which is equal to 20; and

6 The procedure used to estimate the polynomial parameters was the NLIN procedure in SAS. The NLIN procedure computes least squares and weighted least squares estimates of the parameters of a nonlinear model. This procedure requires: the specification of the regression expression, parameter names to be declared, starting values supplied, and for certain algorithms the derivatives of the model with respect to the parameters. The NLIN procedure first examines the starting value specifications of the parameters. If a grid of values is specified, NLIN evaluates the residual sum of squares at each combination of values in order to determine the best set of values to start the iterative algorithm. The iterative methods applied to the trading volume data were the Newton method and the multivariate secant (DUD) method. The Newton method required the specification of the second derivatives of the model with respect to each parameter. The DUD method does not require the derivatives to be prespecified - they are estimated inductively from the history of iterations [Ralston and Jennrich (1978)].
\[ \alpha, \beta, C \text{ and } \gamma \text{ are parameters to be estimated.} \]

These functions were then applied separately to estimate expected intraday trading volume for Mondays, and bull and bear days for the remainder of the week. Expected bull days were defined as days when the observed overnight return on the DJ65 was positive and expected bear days when the overnight return on the DJ65 was negative. An examination of the subsequent intraday evolution of prices showed that if the overnight return on the DJ65 was positive (negative), then intraday AOI and SPI prices continued to steadily increase (decrease) over the course of the trading day. Thus, this ex ante predetermination of the intraday direction of price movements was predictable. The descriptive polynomial model statistics are reported in Table 5.2 for the full data sets. Diagrammatic examples of the relative fit of the polynomial expectations models to the actual intraday trading volumes are presented in Figure 5.2 for a model fitted to all the data and Figure 5.3 for a model fitted to the data from Mondays.

The above descriptive polynomial models form the measure of the expectation of raw trading volume on any specified trading day - bull, bear or Monday. Expected trading volume was calculated by estimating the polynomial functions for the previous observed trading days.\(^7\) Observed trading volume was then subtracted from the expected volume for each specified day and the deviation (DTVP) saved as a measure of the degree of unexpected raw trading volume. The raw trading volume deviations from the two expectation models are reported in Table 5.3. Similar to raw trading volume and raw deviations from the random walk model, the measures of unexpected intraday trading volume are decidedly non-normal and transformation was required.

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7 For the first futures contract, from March to June 1992, this required a holdout sample of futures trading volumes to be collected for the previous contract from January to March 1992. Polynomial functions were then continually reestimated at the end of each month by adding the last months trading data to the data set. In this manner the expectation of trading volume was a function of the type of trading day and past trading volume.
Table 5.2
Intraday Polynomial Descriptive Models of Trading Volume

<table>
<thead>
<tr>
<th>Nonlinear Estimation</th>
<th>Bear Days</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Morning</td>
<td>39.98 + 0.45 (tj - 11.88)^2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.83) (0.15) (1.86)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>R^2 = 0.95</td>
<td></td>
</tr>
<tr>
<td>Afternoon</td>
<td>44.81 + 0.64 (tj - 15.11)^2 + 0.32 (tj - 15.11)^3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00) (0.05) (0.44) (0.00) (0.44)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>R^2 = 0.97</td>
<td></td>
</tr>
<tr>
<td>Bull Days</td>
<td>Model</td>
<td></td>
</tr>
<tr>
<td>Morning</td>
<td>46.50 + 0.74 (tj - 9.81)^2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.92) (0.12) (0.67)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>R^2 = 0.97</td>
<td></td>
</tr>
<tr>
<td>Afternoon</td>
<td>44.58 + 2.07 (tj - 16.39)^2 + 0.50 (tj - 16.39)^3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00) (0.00) (0.11) (0.00) (0.11)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>R^2 = 0.97</td>
<td></td>
</tr>
</tbody>
</table>

| Mondays              | Model     |
| Morning              | 39.65 + 0.55 (tj - 9.38)^2 |
|                      | (3.66) (0.21) (1.90) |
|                      | R^2 = 0.66 |
| Afternoon            | 45.80 + 2.07 (tj - 16.39)^2 + 0.50 (tj - 16.39)^3 |
|                      | (0.00) (0.18) (0.00) (0.00) (0.00) |
|                      | R^2 = 0.94 |

* Numbers in brackets are asymptotic standard errors.
The models reported are derived from the full intraday trading volume data set from January 1992 to March 1993.
Figure 5.2  Comparison of Actual SPI Trading Volume (All Days) with Polynomial Expectations Model
Figure 5.3 Comparison of SPI Monday Trading Volume with Polynomial Expectations Model
Transformation

The problem with applying a simple log transformation is that there are zero and negative values. This is handled by adding a constant to the volume data set [per Richardson, Sefcik and Thompson (1986)] in the following form:

\[
LDTVD = \log [DTVD + C]
\] (5.4)

where C is a constant chosen so that \([DTVD + C]\) is always positive and logs can be taken. The descriptive results from this log transformation, as well as for the raw and log transformations from the residuals derived from the polynomial and random walk intraday models, are reported in Table 5.3. The results confirm that the transformed data better approximates normality.

<table>
<thead>
<tr>
<th>SERIES</th>
<th>MEAN</th>
<th>STDEV</th>
<th>SKEWNESS</th>
<th>KURTOSIS</th>
<th>D:NORMAL</th>
<th>AR1</th>
</tr>
</thead>
<tbody>
<tr>
<td>VOLUME</td>
<td>57.67</td>
<td>48.58</td>
<td>2.64</td>
<td>16.87</td>
<td>0.124</td>
<td>0.33^</td>
</tr>
<tr>
<td>LOG VOLUME</td>
<td>3.72</td>
<td>0.90</td>
<td>-0.81</td>
<td>1.36</td>
<td>0.055</td>
<td>0.19^</td>
</tr>
<tr>
<td>* DTVP</td>
<td>0.95</td>
<td>45.82</td>
<td>2.86</td>
<td>20.35</td>
<td>0.134</td>
<td>0.32^</td>
</tr>
<tr>
<td>LDTVP</td>
<td>4.53</td>
<td>0.38</td>
<td>0.52</td>
<td>0.88</td>
<td>0.057</td>
<td>0.39^</td>
</tr>
<tr>
<td># DTVR</td>
<td>-0.19</td>
<td>60.64</td>
<td>-0.04</td>
<td>12.03</td>
<td>0.082</td>
<td>0.28^</td>
</tr>
<tr>
<td>LDTVR</td>
<td>0.00</td>
<td>1.09</td>
<td>0.05</td>
<td>1.14</td>
<td>0.027</td>
<td>0.19^</td>
</tr>
</tbody>
</table>

^ Significant at the 1% level.
* DTVP is the difference in raw trading volume derived from the intraday polynomial expectations model.
LDTVP is measured as \(\log [DTVD + C]\) where C is chosen to achieve normality.
# DTVR is the difference in raw trading volume using the random walk expectations model.
LDTVR is the log relative measure of deviation measured as \(\log [\text{Vol}_d / \text{Vol}_{d-1}]\).
AR1 is the first order autocorrelation coefficient of the trading volume series.

The next step was to consider whether intraday futures trading volume had an impact on intraday stock and futures returns. This was done by estimating separately the impact of log transformed raw trading volume and alternatively the two measures of unexpected log
transformed trading volume, to the transfer function time series models developed in chapter four for the AOI and SPI returns.

5.5 MODEL FORMULATION AND ESTIMATION

Combining components of trading volume with the time series transfer function model (see chapter four for a complete description of the models) the impact on SPI and AOI returns ($\eta_t$) are modelled as follows:

$$\eta_t = \sum_{i=1}^{q} \Psi_i \eta_{t-i} + \sum_{j=1}^{n} \nu_j(B)X_j + \nu(B) I_t + \sum_{k=0}^{d} \Omega_k T_{t-k} + \varepsilon_t$$  \hspace{1cm} (5.5)

where

- $\sum_{i=1}^{q} \Psi_i \eta_{t-i}$ represents the autoregressive time series effects from previous returns;
- $\sum_{j=1}^{n} \nu_j(B)X_j$ represents both significant return spikes in intraday trading returns and $\nu_j(B)$ the transfer from the return spike;
- $\nu(B) I_t$ represents the impact of an input variable ($I_t$), the overnight return on the DJ65, on $\eta_t$;
- $\sum_{k=0}^{d} \Omega_k T_{t-k}$ is the impact of trading volume on $\eta_t$ which includes contemporaneous as well as lagged prewhitened volumes; and
- $\varepsilon_t$ is the residual term.

Prewhitenning of the trading volume series was undertaken since previous studies showed that trading volume metrics are highly predictable [Ajinkya and Jain (1989), Jain and Joh (1988)]. The first order autocorrelation coefficients (AR1) for all the SPI volume series reported in Table 5.3 confirmed that this is also the case in Australia. In order to control for the predictive ability from the history of past observations the log volume series were transformed by applying an AR filtering process. The residuals from these models can be viewed as part of the series that cannot be predicted from its own history. These prewhitened volume residuals were then applied to the time series transfer function model to test the relation between returns and trading volume.
The previous analysis undertaken in chapter four used transfer function time series models to control for the effects of thin trading in the AOI, bid-ask bounce in the SPI, fixed time of the day effects and the impacts from overnight information. If trading volume has an incremental leading influence on returns then the regression coefficients of the prewhitened volume series will be non zero and positive.

As was the case in chapter four DJ65 represents the previous day’s return on the Dow Jones Composite Stock Index and $\psi_j$ (j = 1,....4), $\delta_j$ (j = 1,....3), and $\gamma$, $\beta$, $\Omega$ are parameters to be estimated. The estimated coefficients, together with their associated t-ratios, for the best fitting model are listed in Table 5.4 for the SPI futures return series.

<table>
<thead>
<tr>
<th>Table 5.4</th>
</tr>
</thead>
</table>

**Results:** Intraday Price Return-Volume Relation in the SPI Futures

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>T Ratio</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Psi_1$</td>
<td>-0.03977</td>
<td>-2.94</td>
<td>Return lag 1 period</td>
</tr>
<tr>
<td>$\Psi_2$</td>
<td>0.03168</td>
<td>2.35</td>
<td>Return lag 4 period</td>
</tr>
<tr>
<td>$\Psi_3$</td>
<td>0.03668</td>
<td>2.71</td>
<td>Return lag 8 period</td>
</tr>
<tr>
<td>$\Psi_4$</td>
<td>0.03882</td>
<td>2.87</td>
<td>Return lag 20 period</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.56309</td>
<td>30.72</td>
<td>US impact at opening</td>
</tr>
<tr>
<td>$\beta$</td>
<td>-0.12508</td>
<td>-3.93</td>
<td>US transfer denominator lag 2</td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>0.03985</td>
<td>3.22</td>
<td>Fixed return 1000</td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>-0.02886</td>
<td>-2.33</td>
<td>Fixed return 1015</td>
</tr>
<tr>
<td>$\delta_3$</td>
<td>-0.02702</td>
<td>-2.19</td>
<td>Fixed return 1430</td>
</tr>
<tr>
<td>$\Omega_0$</td>
<td>-0.02121</td>
<td>-3.20</td>
<td>Volume surprise current(LDTVp)</td>
</tr>
<tr>
<td>$\Omega_1$</td>
<td>0.02138</td>
<td>3.22</td>
<td>Volume surprise lag 1 (LDTVp)</td>
</tr>
</tbody>
</table>

**Residual Analysis**

| Mean | 0.000148 | Variance | 0.03653 |
| Skewness | 0.0372 | Num > 0 | 2735 |
| t for mean = 0 | 0.57 | Schwartz BC | -2498.56 |
| Kurtosis | 6.70 | Number of residuals | 5475 |
| Chi-square lag 24 | 19.70 | Chi-square lag 42 | 25.77 |

The residual analysis from the above model shows that it is a superior model to the one reported in chapter four. The variance of the residuals is lower and the Schwartz information criterion has improved. The Chi-square statistic and the other standard tests confirm that the residuals are well behaved. An analysis of the relation between trading volume and SPI price returns shows the following:
(i) The log of raw trading volume did not have any statistical significant explanatory power for SPI returns.

(ii) Unexpected trading volume from the intraday polynomial model, which takes into account the different intraday volume structures for Mondays and bull and bear trading days, when compared to the random walk model has a greater association with SPI returns.

(iii) Unexpected trading volume has a contemporaneous negative relation with SPI returns and a positive relation with one lag.

Overall, the results suggest that surprises in trading volume led returns in the SPI and have some predictive value over and above the impact of overnight information and confirm the observations of Locke and Sayers (1993).

Table 5.5

<table>
<thead>
<tr>
<th>Intraday Price-Volume Relation between the AOI and Futures Trading</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coefficient</strong></td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
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<tr>
<td>5</td>
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<tr>
<td>6</td>
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<tr>
<td>7</td>
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<td>13</td>
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<td>14</td>
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<tr>
<td>15</td>
</tr>
<tr>
<td>16</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Residual Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Skewness</td>
</tr>
<tr>
<td>t for mean = 0</td>
</tr>
<tr>
<td>Kurtosis</td>
</tr>
<tr>
<td>Chi-square lag 24</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

The proposition that trading volume in the futures market may also have some impact in the stock market is analysed by applying the same model to the AOI returns. The results
are reported in Table 5.5 and show a similar relationship to that reported for SPI returns and surprises in trading volume using the polynomial intraday expectations model. The log of raw trading volume is not significant, contemporaneous surprises in trading volume are negatively related to returns, and surprises in trading volume lagged one period, have a positive relation with AOI returns.

Overall, the results from this addition of trading volume suggest that surprises in trading volume in the SPI futures market lead price returns in the futures and stock market. The relationship is stronger in the futures market but, nevertheless, there is a spillover impact into the underlying stock market.

5.6 CONCLUSIONS

This chapter reported on the analysis of the intraday pattern in trading volume in the SPI futures market. A U-shaped pattern in intraday trading was observed with the intensity of trading the highest during the last ten minutes of trading. Average daily trading volumes were highest on bull days and lowest on Mondays. The lower volume on Mondays resulted from much lower trading in the morning after the long weekend nontrading period.

Intraday polynomial functions were fitted to the trading volumes for Mondays and bull and bear days. It was found that a quadratic function best described trading volume in the morning with a cubic function in the afternoon. Further, the functional form differed between Mondays and bull and bear days.

Unexpected trading volume had a stronger association with returns than raw trading volume. The log of raw trading volume was not significantly related to AOI or SPI returns. The log of the difference between the polynomial models, as measures of expected trading volume, and actual trading volume had greater explanatory power compared to a random walk model. Contemporaneous surprises in trading volume were found to be negatively related to returns and surprises in trading volume lagged one
period had a positive relation with returns. These results suggest that surprises in trading volume lead returns in the SPI and AOI and have additional explanatory power over and above the impact of overnight information.

The volatility of stock and futures markets has long been a concern of regulators, market traders and the public at large. Chapters six and seven now turn to an analysis of interday and intraday volatility and the long term impact of futures derivative trading on stock market volatility.
CHAPTER SIX

SHORT TERM VOLATILITY

6.1 INTRODUCTION

This chapter compares the trading, nontrading and intraday volatility of the All Ordinaries Index (AOI) stock prices with the volatility of the related Share Price Index (SPI) futures prices. An analysis is also undertaken of the impact of private and public information on intraday volatility. An understanding of the process of volatility is fundamental to financial decision making, structural planning and the growth of financial markets. For example, a knowledge of volatility underlies a number of normative theoretical models such as mean-variance portfolio selection, hedging, risk minimisation and option pricing. Secondly, the importance of mapping and understanding the empirical processes of volatility within markets has also been heightened by factors such as the stock market crash of October 1987, the increased trading in derivative security markets and the continued international integration of financial markets. Thirdly, volatility may be caused by any number of factors which have policy implications. For example, the increase in derivative futures trading and capital market integration has led to the examination of 'volatility spillovers' between adjoining or related markets. Further, the trading structure of the market, the arrival of public information, private information trading, trading volume, market clientele, trading halts, uninformed speculation, and market psychology have all been related to price volatility.¹

¹ Suggestions such as trading halts, the elimination of program trading and derivative instruments, the setting of prices by clearing procedures rather than a continuous open outcry system, and the extension
This chapter also concentrates on volatility because it has been suggested that it is the volatility of a security's price, and not the security's price change, that is related to the rate of flow of information [Tauchen and Pitts (1983) and Ross (1989)]. If price changes are interpreted as the market's consensus evaluation of new information, then the corresponding volatility indicates the extent to which traders hold heterogenous evaluations of the new information. Consequently, a knowledge of the time varying properties of price volatility is important for traders, policy makers, and extends our understanding of the dynamic nature of markets.

Volatility based tests of information content also have an advantage in that they are more straightforward in the testing procedure. For example, if an event conveys relevant information to security markets then the volatility during the event period should simply be higher than the non event period. On the other hand, inferences about information content based on measures of price return requires the specification of an expectations model, which in turn determines the unexpected component of information. Therefore, volatility based tests have the advantage that they do not prespecify the sign of returns and hence avoid the errors generated by a (possibly incorrect) specification of subjective expectations models [Yadav (1992, p.158)].

The analysis in this chapter uses the 15-minute data base of the Australian All Ordinaries Index (AOI) and the Share Price Index (SPI) futures contract for the period 1 April 1992 to 30 March 1993 previously described in chapter four. In addition, the Twenty Leaders Index (TLI) for the same period is added to the data base. The chapter makes a contribution to the research literature because it represents one of the first attempts to compare the microstructure of volatility between the cash and futures market in Australia, and to decompose the impacts of private and public information on the significantly larger opening volatilities. The remainder of the chapter is developed as follows. Section 6.2 provides a brief background to the later sections. Section 6.3 examines interday volatility and compares trading and nontrading volatility patterns. Section 6.4 describes
and compares the intraday volatility of the AOI and SPI. This section also adjusts the volatility of the AOI for the nontrading effect, as well as comparing the volatility of the TLI which is an index of well traded stocks and therefore less likely to suffer from nontrading. Section 6.5 uses transfer function time series models to evaluate the relative impact of private and public information on opening volatility. The chapter is concluded in section 6.6.

6.2 BACKGROUND AND RESEARCH PROBLEMS

Several empirical studies have now documented the existence of persistent interday and intraday price patterns in equity and futures markets, particularly the large thickly traded markets of the US and Japan. Previous empirical research in cash stock markets has shown that the average price volatility in trading periods is much higher than nontrading periods [French and Roll (1986)], and the volatility of opening prices is higher than closing prices [Amihud and Mendelson (1987, 1991b)]. Other research has documented that there are spikes in volatility at the opening and closing of trading with the intraday evolution following a rough U-shaped pattern [Wood, McInish and Ord (1985), Harris (1986), McInish and Wood (1991) (US Equity), Chan, Chan and Karolyi (1991), Ekman (1992) (US Futures), Chang, Fukuda, Rhee and Takano (1993) (Japanese Equity), McInish and Wood (1990b) (Canadian equity), Yadav and Pope (1992) (UK equity), and Ho and Cheung (1991) (Hong Kong equity)]. Moreover, the volatility of futures prices is generally higher than those of the underlying cash index series [Park (1993), Chan, Chan and Karolyi (1991), Cheung and Ng (1990)]. One further empirical characteristic is that price changes tend not to be independent, but to exhibit 'volatility clustering'. That is, volatility can be different at different times and tends to cluster together, with large (small) price changes followed by other large (small) price changes but of indeterminate sign.2

2 This phenomena has motivated the development of Engle's (1982) Autoregressive Conditional Heteroscedasticity (ARCH) model and the extension into the general (GARCH) model by Bollerslev (1986). There is now a large body of evidence that applies the ARCH family of time series models to the dynamic behaviour of stock return volatility [see the review by Bollerslev, Chou and Kroner...
One potential factor which have been proposed as a cause of volatility is the microstructure of the market or the existence of different trading mechanisms. The studies by Amihud and Mendelson (1987, 1991a, 1991b) suggest that price volatility is higher in a continuous open outcry market compared to a periodic clearing market. Given these results, one may expect to observe a higher volatility in the SPI futures market which is an open outcry clearing auction, than in the AOI cash market, which is a more controlled computer based dealership market. In addition, trading halts have been hypothesised to affect price volatility in security markets. A remedy often cited is to implement circuit breakers that halt trading when markets become excessively volatile [Greenwald and Stein (1991)]. Other researchers suggest that circuit breakers increase the uncertainty regarding the ability to exit the market and that an environment with trading halts may be less stable than an environment without halts [Gerety and Mulherin (1992)]. Security markets experience a natural circuit breaker between the close of trading on one day and the opening of trading on the subsequent morning. The Australian futures market, unlike overseas futures markets, experiences an additional trading halt when the market closes for lunch from 1230 to 1400 every trading day. The analysis of the impact of opening price setting mechanisms and the process of intraday volatility is undertaken in section 6.3.

Another important factor that may affect volatility is the degree of nonsynchronous trading or the thinness of the stock market. The AOI is a broadly based stock index containing some 250 stocks. By international standards the Australian stock market is very thin and many stocks do not trade consistently every day [Hathaway (1986)]. The greater the nontrading of stocks in the AOI, the more it represents an average of stale historical prices rather than current prices. This factor induces differences in the reaction times of cash indices and futures to new information and may cause the AOI to be less volatile than it would be if it reflected current prices. The relative volatilities of cash and futures, after adjustments for thin trading, are analysed in section 6.4.
French and Roll (1986) first conjectured that higher trading time price volatility could be induced by public information or the release of private information through the trading activities of informed investors. They concluded that trading time volatility was mainly related to private information. Since the seminal study of French and Roll there have been a number of researchers who have debated the relative importance of overnight public information and private information as a cause of price volatility. Admati and Pfleiderer (1988) predicted that private information traders are more active at the start and end of the day and this is related to volatility clustering during these periods. Herbst and Maberly (1992) argued that end of the day price volatility is positively related to the next morning's opening volatility and to private information gathering. Amihud and Mendelson (1991b) and Park (1993) suggested that the higher volatility in the morning is related to public information created during the overnight nontrading period. One objective of this chapter is to decompose the relative importance of public and private information on opening and subsequent volatility. This is done by fitting impulse transfer functions to the previous nights closing volatility (as a proxy for private information) and an intervention and transfer function to the overnight volatility from the US stock market (as a proxy for public information), and analysing the relative impacts on the subsequent mornings volatility. These descriptive intraday volatility patterns are reported in section 6.4 and the relative impact of private and public information is analysed in section 6.5.

It is important to point out that the link between incremental private and public information content and price volatility depends upon the assumption that security price reactions are informational rational. As outlined in chapter two there is a considerable literature outlining arguments that excessive or noise volatility is related to speculation or market psychology. For example, the October 1987 stock market crash has been interpreted as the breaking of a speculative bubble [Stiglitz (1990)]; White (1990) provides arguments that the boom and bust of the 1920's was mainly driven by speculative elements; De Bont and Thaler (1985, 1987) and Pettergill and Jordan (1990) contend that investors overreact to security prices; Baumol (1957) and Shleifer and
Summers (1990) suggest that speculators tend to jump on the 'bandwagon' or focus on single pieces of information [Froot, Scharfstein and Stein (1992)] which results in volatility spillover.

After adjustment for nontrading a number of previous studies have found that the volatility of the futures market is still higher than the volatility of the underlying AOI stock market. There are two common interpretations of this result. One is that 'noise traders' are more active in the futures markets, so temporary price movements are exaggerated. The alternative is that futures contract prices react more quickly to new information because the contracts have lower transaction costs and because they price the bundle of underlying stocks simultaneously. The analysis undertaken in section 6.5 filters out the impact of information on volatility, thereby allowing some assessment to be made of the relative importance of these factors.

The Australian cash and futures markets provide an excellent laboratory for investigating the effect of particular market microstructures, mechanisms and information flows on price volatility because of several unique features. Since September 1990 the Australian Stock Exchange has been fully computerised and prices are set by matching screen quotes which are driven by demand and supply in the market place. This system is in contrast to the specialist quote driven system applied in the US stock market. Further, the Sydney Futures Exchange continues to set prices by a continuous open outcry system in a trading pit. Secondly, the cash market trades continuously from 1000 to 1600, whilst the futures market opens 10 minutes earlier at 0950, closes 10 minutes later at 1610, and halts for lunch from 1230 to 1400 and then later re-opens for overnight computer trading. Thirdly, the Australian market is not traded at the same time as the US and UK markets, and therefore, the opening volatility may be affected by a potentially larger accumulated public information set. Fourthly, the Australian stock market is thinly traded and this factor allows tests to be carried out on the comparative price volatility of well traded and thinly traded markets.
6.3 INTERDAY, TRADING AND NONTRADING VOLATILITY

6.3.1 Data and Methodology

The methodology used in this section is primarily based on comparing the variance of returns for the AOI and SPI. The returns are measured over 24-hour periods and various nontrading and trading periods. By using a 24-hour period the total flow of information is controlled for and the effects of trading mechanisms can be isolated. Examples of studies that use these 24-hour variance ratios are Amihud and Mendelson (1987), Stoll and Whaley (1990b), and Masulis and Ng (1991). These studies calculated the variance ratio for each stock. Inferences were then made by an estimation of the average variance ratio across stocks and the cross sectional standard deviation and standard error. The empirical evidence suggested that opening returns are more volatile than closing returns for each of the markets examined.

The basic methodology is to calculate variance ratios using the logarithm of the price relatives as a measure of returns. For the interday analysis a sequence of intraday prices can be used to calculate 24-hour returns. For example, the open-to-open continuously compounded returns for the AOI are calculated as:

\[ R_{o,t} = \ln (P_{o,t}) - \ln (P_{o,t-1}) \]  

(6.1)

where \( P_{o,t} \) is the AOI opening price and \( P_{o,t-1} \) is the previous day's opening price which for the AOI is at 1000. Using the sequence of intraday price observations, returns may be calculated for any desired 24-hour period such as close-to-close, 1100-to-1100, and so on. All information that changes prices is equally reflected in any 24-hour return series and, therefore, differences in the volatility of returns may be attributed to the effects of different trading procedures, times or trading clientele; rather than information flows. The variance ratio for the opening and closing price returns is constructed as follows:


\[ V = \left[ \sigma_o^2 / \sigma_c^2 \right] = \left[ \text{Var} \left( R_{o,t} \right) / \text{Var} \left( R_{c,t} \right) \right] \]  

(6.2)

where \( R_{o,t} \) is the 24-hour continuously compounded return based on opening prices, \( R_{c,t} \) is the 24-hour continuously compounded return based on closing prices, and \( \sigma_o^2 \) and \( \sigma_c^2 \) are the corresponding variance of returns. A similar methodology is applied to analyse the volatility of returns in nontrading and trading periods. Each day the price data is divided into five time intervals and returns defined by:

\[
\begin{align*}
RN_t &= \ln (P_{mo,t}) - \ln (P_{ac,t-1}) \\
RM_t &= \ln (P_{mc,t}) - \ln (P_{mo,t}) \\
RL_t &= \ln (P_{ao,t}) - \ln (P_{mc,t}) \\
RA_t &= \ln (P_{ac,t}) - \ln (P_{ao,t}) \\
RD_t &= \ln (P_{ac,t}) - \ln (P_{mo,t})
\end{align*}
\]

where mo is morning opening, mc is morning close, ao is afternoon opening and ac is afternoon close. Correspondingly, RN is the overnight return, RM is the morning return, RL is the lunchtime return, RA is the afternoon return, and RD is the return over the trading day between the opening and closing. Variance ratios are calculated in the same manner as equation (6.2).

6.3.2 Interday Patterns in Volatilities

The purpose of this section is to analyse and compare the effects of different trading mechanisms on the short term price volatility in cash and futures markets. Specifically, the effects of the opening price setting mechanisms and the trading halt over lunch in the futures market.

Amihud and Mendelson (1987, 1991a, 1991b) studied the relative price volatility of opening prices for a number of stock markets. They found that whilst the opening transaction had a greater volatility than the closing transaction, this difference is greater when the first transaction of the day is executed in a continuous trading mechanism.
They further concluded that opening the market with a clearing transaction provided a more efficient value discovery mechanism and recommended to policy makers that a clearing transaction, rather than a continuous market, be used to determine opening prices.

In this section the methodology used is the same as Amihud and Mendelson which allows a direct comparison with the overseas studies. Opening prices in the Australian stock market are set by a lagged matching process (see Appendix 2.1) which takes up to nine minutes to determine the opening price. In contrast the SPI futures market uses an open outcry system to determine the opening price. Thus, a comparison of open-to-close volatilities in futures is a further test of whether the higher volatility observed in cash markets at opening is caused by the price setting mechanism or by the accrual of information during the prior period of no trading. Additionally, the comparison of 1230-to-close and 1400-to-close price volatilities extends the tests applied by Amihud and Mendelson to an analysis of the effects of a trading halt on futures prices. If traders in the futures market face increased uncertainty because of their inability to exit the market over lunch, it is predicted that futures prices at or around the predictable lunch time halt will reflect greater instability when compared to cash prices which continue to be traded.

The effects of the trading mechanisms and time of trading on 24-hour return volatility were examined for the SPI futures and AOI stock market and the results reported in Table 6.1. Panel A compares intraday 24-hour return variances with the variance of close-to-close returns. Panel B reports first order autocorrelation coefficients of the 24-hour return series.

The variance ratios for the SPI indicate a general decline in volatility over the trading day. In particular, the variance ratio of the open-to-open SPI returns is 6.7% greater than the volatility of the close-to-close returns. In the cash stock market the same variance ratio is 1.8% higher and the variance ratios for the AOI cash market follow a different pattern. They increase during the first half hour of trading and, unlike the futures, stay consistently above a ratio of one over the course of the trading day.
Based on the observation that the relative interday variance of opening to closing prices in
the futures market is almost 5% higher than the cash market, an initial conclusion might
be that the use of the more orderly bid/ask matching procedure (in contrast to the
continuous open outcry system of the futures market) leads to a lower relative volatility at
the opening of trading. It is not clear, however, that this structured approach provides a
more efficient price discovery mechanism if it only serves to delay the volatility impact.
By extending the analysis to the following intraday observations we can observe any
delay effects.

Using the 1015-to-1015 observation as an indicator of the lag effect shows that the
variance of the AOI returns exceed the variance of the close-to-close cash returns by
some 18.5%. This lagged variance ratio is consistent with the 20% and 15% higher
open-to-open price variances over the close-to-close variances on the New York Stock
Exchange and Tokyo Stock Exchange observed by Amihud and Mendelson (1987,
1991a). The further observation that the open-to-close variance ratio is one of the lowest
of the day suggests that the opening price setting procedure employed in the Australian
stock market fails to quickly reflect overnight information.

Efficiency and the speed of price adjustment to new information have also been related to
autocorrelation patterns. If past returns have no information content and prices react
instantly to new information then autocorrelations should be zero [Fama (1976)]. The
first order autocorrelation coefficients of various 24-hour price returns are summarised in
panel B of table 6.1. Autocorrelations for futures returns generally follow an inverted U-
shaped pattern with open-to-open, 1000-to-1000, and close-to-close returns exhibiting
negative autocorrelation. Autocorrelations for the AOI returns are all positive with all but
the 1015-to-1015 (open+1), 1030-to-1030, and 1045-to-1045 returns statistically
significant. The general trend, in both markets, is for the sign of the autocorrelation
coefficient to increase over the trading day and this is especially the case during the
morning session. This result is consistent with previous research which proposed that
low or negative autocorrelations are associated with value discovery or the incorporation
### Table 6.1
VOLATILITIES AND AUTOCORRELATIONS BY INTRADAY 24-HOUR PERIODS

#### Panel A - 24 Hour Variance Ratios

<table>
<thead>
<tr>
<th>Time of the Day Ratio</th>
<th>SPI Variance Ratios</th>
<th>AOI Variance Ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td>0950/Close</td>
<td>1.067</td>
<td>-</td>
</tr>
<tr>
<td>1000/Close</td>
<td>1.017</td>
<td>1.018</td>
</tr>
<tr>
<td>1015/Close</td>
<td>0.938</td>
<td>1.185</td>
</tr>
<tr>
<td>1030/Close</td>
<td>0.979</td>
<td>1.204</td>
</tr>
<tr>
<td>1045/Close</td>
<td>0.928</td>
<td>1.175</td>
</tr>
<tr>
<td>1100/Close</td>
<td>0.932</td>
<td>1.158</td>
</tr>
<tr>
<td>1115/Close</td>
<td>0.874</td>
<td>1.130</td>
</tr>
<tr>
<td>1130/Close</td>
<td>0.863</td>
<td>1.108</td>
</tr>
<tr>
<td>1145/Close</td>
<td>0.838</td>
<td>1.083</td>
</tr>
<tr>
<td>1200/Close</td>
<td>0.851</td>
<td>1.086</td>
</tr>
<tr>
<td>1215/Close</td>
<td>0.816</td>
<td>1.045</td>
</tr>
<tr>
<td>1230/Close</td>
<td>0.868</td>
<td>1.059</td>
</tr>
<tr>
<td>1400/Close</td>
<td>0.960</td>
<td>1.158</td>
</tr>
<tr>
<td>1415/Close</td>
<td>0.915</td>
<td>1.136</td>
</tr>
<tr>
<td>1430/Close</td>
<td>0.956</td>
<td>1.158</td>
</tr>
<tr>
<td>1445/Close</td>
<td>0.885</td>
<td>1.113</td>
</tr>
<tr>
<td>1500/Close</td>
<td>0.885</td>
<td>1.070</td>
</tr>
<tr>
<td>1515/Close</td>
<td>0.897</td>
<td>1.059</td>
</tr>
<tr>
<td>1530/Close</td>
<td>0.863</td>
<td>1.048</td>
</tr>
<tr>
<td>1545/Close</td>
<td>0.874</td>
<td>1.003</td>
</tr>
<tr>
<td>1600/Close</td>
<td>0.899</td>
<td>-</td>
</tr>
</tbody>
</table>

# The variance ratio is calculated as the variance of the specified 24-hour return divided by the variance of the close to close return.

#### Panel B - 24 Hour First Order Autocorrelations of Returns

<table>
<thead>
<tr>
<th>24-Hour Period</th>
<th>SPI First Order Autocorrelations</th>
<th>AOI First Order Autocorrelations</th>
</tr>
</thead>
<tbody>
<tr>
<td>0950-to-0950</td>
<td>-0.055</td>
<td>-</td>
</tr>
<tr>
<td>1000-to-1000</td>
<td>-0.025</td>
<td>0.125*</td>
</tr>
<tr>
<td>1015-to-1015</td>
<td>0.012</td>
<td>0.055</td>
</tr>
<tr>
<td>1030-to-1030</td>
<td>0.001</td>
<td>0.085</td>
</tr>
<tr>
<td>1045-to-1045</td>
<td>0.051</td>
<td>0.101</td>
</tr>
<tr>
<td>1100-to-1100</td>
<td>0.047</td>
<td>0.112**</td>
</tr>
<tr>
<td>1115-to-1115</td>
<td>0.113**</td>
<td>0.135*</td>
</tr>
<tr>
<td>1130-to-1130</td>
<td>0.095</td>
<td>0.153*</td>
</tr>
<tr>
<td>1145-to-1145</td>
<td>0.096</td>
<td>0.144*</td>
</tr>
<tr>
<td>1200-to-1200</td>
<td>0.085</td>
<td>0.133*</td>
</tr>
<tr>
<td>1215-to-1215</td>
<td>0.126*</td>
<td>0.165*</td>
</tr>
<tr>
<td>1230-to-1230</td>
<td>0.091</td>
<td>0.161*</td>
</tr>
<tr>
<td>1400-to-1400</td>
<td>0.024</td>
<td>0.106*</td>
</tr>
<tr>
<td>1415-to-1415</td>
<td>0.060</td>
<td>0.135*</td>
</tr>
<tr>
<td>1430-to-1430</td>
<td>0.049</td>
<td>0.144*</td>
</tr>
<tr>
<td>1445-to-1445</td>
<td>0.087</td>
<td>0.169*</td>
</tr>
<tr>
<td>1500-to-1500</td>
<td>0.070</td>
<td>0.190*</td>
</tr>
<tr>
<td>1515-to-1515</td>
<td>0.065</td>
<td>0.184*</td>
</tr>
<tr>
<td>1530-to-1530</td>
<td>0.076</td>
<td>0.177*</td>
</tr>
<tr>
<td>1545-to-1545</td>
<td>0.060</td>
<td>0.187*</td>
</tr>
<tr>
<td>1600-to-1600</td>
<td>0.024</td>
<td>0.188*</td>
</tr>
<tr>
<td>1610-to-1610</td>
<td>-0.016</td>
<td>-</td>
</tr>
</tbody>
</table>

The first order autocorrelation is estimated from the time series of the specified 24-hour return.

* significant at 5% level

** significant at 10% level
of information into prices. The lower autocorrelation of the 1015-to-1015 AOI return together with the lagged increased volatility suggests that the controlled bid/ask clearing transaction used to set opening prices in the Australian stock market may only serve to postpone the increased volatility until 1015. These prices, although more volatile, may in fact act as a more efficient value discovery mechanism.

The effects of the mid-day trading halt in the futures market are also examined by reference to table 6.1. A comparison of the variance ratios in the futures market and the stock market at 1230 shows a slight increase in the AOI and SPI variance ratios at 1230 before the futures lunchtime close. After resumption of futures trading at 1400 the variance ratio in both markets jumps by about 10%. An examination of the autocorrelation pattern shows a drop in the autocorrelations from 1230 to 1400. The major overall effect of the lunchtime close is an increase in volatility and a reduction in autocorrelation in the futures market upon resumption at 1400. This is consistent with some information theories which predict higher volatility and lower autocorrelation with the incorporation of information in prices. However, the same general pattern occurs in the stock market at 1400 even though trading is not halted over this period. This is consistent with a feedback effect from the futures to the stock market to a lack of activity in the stock market.

6.3.3 Volatility in Trading and Nontrading Periods

This section extends the analysis of French and Roll (1986) on the sources of volatility in stock markets. French and Roll suggested that price volatility can be caused by individual investors who interact with each other and reveal private information, by the release of public information, or by the overreaction to each other's trades. French and Roll tested their hypothesis by comparing price volatility in trading periods to price volatility in nontrading periods. They found that the volatility on the NYSE during trading hours was 71.8 times greater than volatility during weekend nontrading and 13.2 times greater than mid-week nontrading periods. These results, however, failed to determine whether the higher trading volatility reflected trading induced volatility, or the
fact that the arrival of public information may be more frequent during the business day' [French and Roll (1986, p.23)].

This section provides further evidence on this issue by comparing the hourly volatility over trading and nontrading periods within the business day in addition to a comparison of the overnight nontrading volatility with trading volatility. Nontrading volatility during the business day in the futures market is also compared to trading time volatility in the cash market. This comparison is possible in Australia, because of the lunchtime closure of the futures market.

If information arrives uniformly during the calendar day and volatility is only generated by the arrival of new information, then return variances should be the same for equally spaced trading and nontrading periods during the day. If trading activity contributes to volatility through the dissemination of private information or traders overreaction, and this phenomena is more prevalent in futures markets, then the relative volatility in futures during trading periods should be higher.

Table 6.2 presents a number of measures of volatility. The standard deviation of returns and the average hourly return variances for five time intervals; the two daytime trading periods, the lunchtime period which is a trading period in the cash market and a nontrading period in the futures, an overall trading day average and the overnight nontrading period. The average hourly return variances for the trading periods are 10.7 times greater in the futures market and 7.9 times greater in the cash stock market, than the average overnight nontrading period variance. Although lower than the results of French and Roll, it confirms the prediction of a higher trading time variance and is very similar to the results of Amihud and Mendelson (1989) who found a trading time per-hour variance 7.2 times larger than the overnight variance on the Tokyo Stock Exchange.
Table 6.2
TRADING AND NONTRADING PERIOD VOLATILITY

<table>
<thead>
<tr>
<th>Period</th>
<th>SPI</th>
<th>AOI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overnight</td>
<td>0.554</td>
<td>0.398</td>
</tr>
<tr>
<td>Morning</td>
<td>0.609</td>
<td>0.448</td>
</tr>
<tr>
<td>Lunch</td>
<td>0.160</td>
<td>0.114</td>
</tr>
<tr>
<td>Afternoon</td>
<td>0.526</td>
<td>0.314</td>
</tr>
<tr>
<td>Trading Day</td>
<td>0.850</td>
<td>0.559</td>
</tr>
<tr>
<td>To overnight period</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overnight</td>
<td>0.140</td>
<td>0.066</td>
</tr>
<tr>
<td>Morning</td>
<td>1.389</td>
<td>0.803</td>
</tr>
<tr>
<td>Lunch</td>
<td>0.171</td>
<td>0.086</td>
</tr>
<tr>
<td>Afternoon</td>
<td>1.277</td>
<td>0.493</td>
</tr>
<tr>
<td>Trading Day</td>
<td>1.496</td>
<td>0.521</td>
</tr>
</tbody>
</table>

Average Hourly Variance (x100)

<table>
<thead>
<tr>
<th>Period</th>
<th>Variance Ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td>Morning</td>
<td>9.92</td>
</tr>
<tr>
<td>Lunch</td>
<td>1.22</td>
</tr>
<tr>
<td>Afternoon</td>
<td>9.12</td>
</tr>
<tr>
<td>Trading Day</td>
<td>10.69</td>
</tr>
<tr>
<td>To overnight period</td>
<td></td>
</tr>
<tr>
<td>Morning</td>
<td>8.12</td>
</tr>
<tr>
<td>Afternoon</td>
<td>7.47</td>
</tr>
<tr>
<td>Trading Day</td>
<td>8.75</td>
</tr>
</tbody>
</table>

The variance ratio is calculated as the ratio of average hourly variances.

Table 6.3
FIRST ORDER AUTOCORRELATION OF RETURNS

<table>
<thead>
<tr>
<th>Period</th>
<th>Autocorrelations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SPI</td>
</tr>
<tr>
<td>Overnight</td>
<td>-0.074</td>
</tr>
<tr>
<td>Morning</td>
<td>0.058</td>
</tr>
<tr>
<td>Lunch</td>
<td>-0.048</td>
</tr>
<tr>
<td>Afternoon</td>
<td>-0.115</td>
</tr>
<tr>
<td>Trading Day</td>
<td>-0.047</td>
</tr>
</tbody>
</table>

* Significant at 5% level

The average morning and afternoon hourly variances are similar in the futures market, but in the stock market the morning variance ratio is about 60% higher than the afternoon variance. The hourly variances during lunch have fallen significantly for both the futures and cash markets. The lunchtime variance ratios, however, are still 20-30% higher than the per-hour return variance during the overnight period. Finally, it is worth noting that the hourly variances and the percentage standard deviations of the period returns are much higher for the futures market compared to the stock market. The comparative per-hour futures to cash variances in morning trading are about 70% higher, in afternoon trading are 160% higher, and in the overnight period the futures are more than double the
cash variances. The futures market also appears to have a more persistent volatility structure than the stock market. That could be related to consistent private information gathering or to continuous speculation.

Of further interest is the first order autocorrelation of returns during trading and nontrading periods. In the futures market none of the autocorrelation coefficients are significant and they tend to be negative in sign. One characteristic to note is that the autocorrelation coefficient for the morning trading return is positive but changes sign during the afternoon trading session. The cash market shows a similar autocorrelation structure during the two major trading sessions. Morning trading session returns are positively autocorrelated and large (0.21) and afternoon returns negatively autocorrelated (-0.14). During the overnight and lunchtime periods, when there is little or no trading, the autocorrelation is not statistically different from zero. Overall these observations can be summarised as follows:

(i) there is a greater intensity of volatility during the trading day compared to the overnight nontrading period;
(ii) the volatility in the stock market is concentrated in the morning session;
(iii) the volatility in the futures market is higher and more persistent than the stock market;
(iv) the rate of arrival of information during lunchtime is lower, or that traders in the cash market are disinclined to trade and informed traders are less likely to trade on their private information; and
(v) the autocorrelation structure of returns differs over periods. In the morning the first order autocorrelations of returns are positive and in the afternoon they are negative. The relationship is statistically significant and stronger in the cash market.

To examine the possibility of a 'weekday effect' volatilities were decomposed into days of the week. Of particular interest in Australia are the effects of overnight trading from the US market. In the cash and futures markets both hourly variances and variance ratios are higher on Monday and Tuesday mornings. This is to be expected as trading in these
periods follow a long weekend nontrading halt and the resumption of trading in overseas markets. Moreover, the effect lingers on through the lunchtime periods on Monday and Tuesday when variance is higher than the overnight nontrading period and the variance ratios, which compare lunchtime volatility to other trading time volatilities, are low. For the remainder of the week lunchtime volatility is lower than overnight hourly variance with the exception of Friday in the SPI. This suggests that the higher lunchtime per-hour variance is a residual effect induced by the information effects from the long weekend nontrading period and the resumption of trading in overseas markets. These observations tend to strengthen the argument that trading, per se, causes volatility but that volatility is also related to information flows.

6.4 INTRADAY VOLATILITY

6.4.1 Intraday Patterns

In order to better understand the microstructure of the volatility process, this section documents the intraday volatility of 15-minute returns for the AOI and SPI. Returns are calculated as the log relative of 15-minute prices and the variance of returns and squared returns are used as proxies for intraday volatility. Figure 6.1 plots the intraday variance and squared returns for the SPI and AOI as a distinct L-shaped pattern. The nontrading overnight variance of 0.3033 for the SPI is about ten times greater than the average interior trading time volatilities. The higher opening variances were consistent across the days of the week with Monday morning (weekend) the highest at 0.384 and the Friday morning variance the lowest at 0.221. After the initial high overnight volatility, the variances slowly decline during the morning and reach a low point of 0.020 at the close of morning trading at 1230. Volatility in the afternoon trading period was relatively stable with a slight upkick during the last trading period from 1600 to 1610. The plot of squared returns was similar. For example, opening squared returns were about ten times

---

3 Variances are multiplied by 10⁴ to aid readability.
the interior, the lowest point was at 0.010 at 1230, and there was a slight upkick at 1015 and at the close (0.018).

Decomposition of the SPI into bull and bear days showed little change in the variance pattern. The exception was the overnight variance on bear days which was lower at 0.24 and slightly higher during bull days at 0.33. Other than these exceptions, the intraday variance pattern in SPI futures was not changed by the direction of price movement over the day.

The patterns in AOI cash volatility were similar to the SPI. Overnight variances averaged 0.178 which was about sixteen times the average trading time variances. After the first half hour of trading the variance dampens down to reach a low point at 1230 and remained fairly constant during the afternoon in a range from about 0.007 to 0.009. Similar to the SPI there was a very slight upkick at close of trading but it was not of the magnitude observed in overseas equity markets. Similar to the SPI, the decomposition into bull and bear days did not have any material effect on the pattern of volatility in AOI returns. The close similarity of the patterns for intraday variances and squared returns suggested that either measure can be applied as a proxy for intraday volatility.

One important observation is that contemporary short term volatility is consistently higher in the futures market when compared to the stock market. Table 6.4 reports the relative intraday volatilities calculated as the ratio of futures market volatility to cash market volatility (SPIv/AOIv). The ratios calculated in Table 6.4 are all contemporary except for the opening and closing ratios. Taking into account the fact that the futures market opens ten minutes earlier at 950 and closes ten minutes later at 1610, the 1000 and 1600 futures volatility were dropped and, therefore, the opening ratio is SPIv,950/AOIv,1000 and the closing ratio SPIv,1610/AOIv,1600.

Bull days are defined as days when \( P_{10} < P_{tc} \) and bear days when \( P_{10} > P_{tc} \), where \( P_{10} \) is the opening futures price and \( P_{tc} \) is the closing futures price.

All of the descriptive analysis was repeated for standard deviations and absolute returns with similar L-shaped patterns resulting. However, the opening standard deviations and absolute returns were about four times average interior volatilities which is close to the results of similar US studies (see Figure 6.2 at the end of the chapter).
Squared Returns

Variance of Returns

*Volatilities multiplied by 10^4

Figure 6.1 Intraday volatility of the AOBJ and SPI
### Table 6.4
**INTRADAY RELATIVE VOLATILITY RATIOS**

<table>
<thead>
<tr>
<th></th>
<th>SPI/AOI 1</th>
<th>SPI/AOI Bull 2</th>
<th>SPI/AOI Bear 3</th>
<th>TLI/AOI 4</th>
<th>SPI/TLI 5</th>
<th>*Merton/AOI 6</th>
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<tr>
<td><strong>Open</strong></td>
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<td>1.56</td>
<td>2.28</td>
<td>0.83</td>
<td>2.07</td>
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<td>1.49</td>
<td>1.12</td>
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<td>2.04</td>
<td>0.96</td>
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<td>4.04</td>
<td>2.04</td>
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<td>2.22</td>
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</tr>
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<td>1.77</td>
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<td>1.66</td>
<td>1.99</td>
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<td>3.06</td>
<td>1.96</td>
<td>1.49</td>
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<td>2.02</td>
<td>1.46</td>
<td>1.46</td>
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<tr>
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<td>3.06</td>
<td>1.93</td>
<td>1.51</td>
<td>1.42</td>
</tr>
</tbody>
</table>

*Relative volatilities are measured as a variance ratio of the past period price change with futures variance the numerator. For example in the first column the ratio is υ = [σ^2_{spi} / σ^2_{aoi}] = [Var(R_{spi}) / Var(R_{aoi})].

*Note that the 1000 and 1600 volatilities are excluded for the SPI. Opening and closing observations are 950 and 16 for the SPI and 1000 and 1600 for the AOI and TLI.

*The Merton adjustment is made by multiplying observed AOI variance by [1 + 2p] where p is the intraday correlation coefficient (see footnote 7).

On average, the relative SPI/AOI variance ratio is 2.96 which indicates that the futures market is almost three times more volatile over the trading day than the stock market.

The relative volatilities are smallest at the start of morning trading and at 1400 after the lunchtime trading break, and largest at 1230 but otherwise fairly stable throughout the day. Average morning and afternoon volatility ratios are almost the same. The volatility ratio is also consistent across weekdays with average volatility in the futures market consistently about three times higher with slightly higher average volatility in the afternoon. The results suggest that the relative volatilities decline at or around trading
halts or the arrival of public information over nontrading periods. The relative volatilities are highest during the interior trading periods which supports the proposition that there is higher inherent volatility in futures. This may be a function of greater private information gathering ability or noise trading in futures.

The relative bull and bear day variances are reported in columns two and three in Table 6.4. They indicate that during bull trading days relative volatility increases on average by about 10-13% when compared to bear days. Of particular note is that the relative opening overnight volatility is 56% higher on bull days compared to bear days. This suggests that futures markets have a larger reaction to 'good' news.

### 6.4.2 Thin Trading and Stock Index Volatility

One result which comes through strongly from the above analysis is the volatility of the futures market is higher than the cash market. Comparisons, however, of the SPI traded on the futures market and the AOI are confounded by nonsynchronous trading problems and the higher volatility might be due to thin trading rather than to some other structural feature of the market. The AOI is a broadly based index comprising some 250 stocks and many of the stocks will not have traded during intervening postings of AOI values. If the nonsynchronous trading effect is significant then it will induce an index which is less volatile than it would be than if contemporary values were considered.

In order to assess the scope of this problem the variance of the AOI is compared to the variance of the Twenty Leaders Index (TLI). The TLI is a capitalised index which measures the price performance of the 20 largest stocks listed on the ASE which are heavily traded and, hence, the TLI reflects changes in value relatively quickly. The results are reported in column four Table 6.4 and shows, on average, the TLI is about twice as volatile as the AOI. The opening overnight return has the highest relative volatility and 1015 the lowest and this may be a reflection of the way in which the stock market is opened in Australia (see Chapter 2). For the remainder of the trading day the

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6 See Hathaway and Officer (1990) who discuss a number of issues related to thin trading in Australia.
relative volatility remains consistently above the AOI. It is also interesting to compare the relative volatilities between the TLI and SPI in column five. On average the variance in the futures is 49% higher, but over the first 40 minutes of trading there appears to be much less difference. It should, however, be noted that direct comparisons of the SPI and TLI volatility (as a surrogate for true sharemarket volatility) are not strictly valid. The TLI comprises only about 50% of the market value of the AOI and the volatility structure of the remaining smaller stocks may not mirror the TLI.

An alternative would be to adjust the AOI directly to reflect the nontrading effect. Merton (1980) suggested an adjustment process to lever variance estimates by assuming an autocorrelation lag of three. Merton found that 99.6% of his adjustment factor was accounted for by the first order autocorrelation effect and the contribution of the second and third lags was insignificant. Using these results, the volatility of the AOI was adjusted by applying a one lag model and multiplying the observed AOI variance by \((1 + 2\rho)\) where \(\rho\) was the calculated serial correlation coefficient.\(^7\) The estimate of the \(\rho\) correlation took into account the observation that the correlation structure of the AOI returns was not static over the course of the trading day. It was found that intraday correlations for the AOI were all positive but followed an inverted U-shaped pattern. They were lower in the early morning and towards the close of trading and confirmed the prediction that higher trading volume would reduce the level of intraday serial correlation [Martell and Trevino (1990)]. The observations of Merton were also confirmed in that only the first lag correlation coefficient for most observations was significant. The ratio of the adjusted AOI variances to the raw AOI variances are reported in column six of table 6.4. They show the levered volatility of the AOI has been increased by an average of 44%.

\(^7\) A derivation of the Merton adjustment procedure is outlined in Merton (1980) and applied to Australian data by Hathaway (1986, Appendix B). It is also a specific case of the adjustment procedure suggested by this thesis in Appendix 7.1. Assuming that the constant first order autocorrelation coefficient for the AOI series was 0.238 then the adjustment factor would be 1.476. Therefore, true variances would be increased by 47.6% over observed variances and standard deviations increased by 21.5%.
The above analysis confirms that the AOI has a reduced volatility which can be partly attributed to thin trading in the Australian stock market. Depending on the adjustment method, this structural feature accounts for between 23% to 49% of the difference in volatility between the SPI futures and the AOI. When the TLI and the Merton adjusted AOI volatilities are compared to the SPI, there is a smaller divergence during the first 40 minutes of trading and greater comparative volatility in the later part of the trading day. This evidence suggests three conditional conclusions: (i) the excess volatility of the futures market is not fully explained by thin trading in the AOI (ii) the volatility at the beginning of trading is probably related to public information arrival and/or private information trading, and (iii) the persistent high volatility throughout the remainder of the day in futures may be related to the structure of trading or the clientele in the futures market. Whether the higher short term variance in the SPI spills over and affects the volatility of the AOI is considered in chapter seven. The next section examines the impact of private and public information flows on opening volatility.

6.5 PRIVATE AND PUBLIC INFORMATION AND VOLATILITY

There are continuing and important debates in the literature about a number of issues which are considered in this section. The first is the relative importance of private and public information as an explanation for the observed high opening volatilities. The second is the role of the futures market as a price discovery or as a conduit for transmitting information. The third relates to the higher volatility observed at the end of the day. Conjectures range from a rational price discovery function through to the perception that it is a function of the higher risks from holding open positions overnight or reflect the actions of day traders or speculators who automatically close positions at the end of the day. The background to the empirical research undertaken in this section is now briefly outlined.
6.5.1 Overnight Information and Volatility

Grossman (1977) argued that the incentive to invest in private information gathering is inversely related to the forecasting ability of the current price to predict ex ante prices. An important theoretical distinction is made between private and public information. Public information is information which is (theoretically) freely available and publicly observable. In contrast, private information is gathered by a relatively few individuals and becomes publicly observable through the trading process and the movement of prices. Grossman and Stiglitz (1980) hypothesised that the greater is the relative ratio of private information traders, the more informative is the price system. Ross (1989) demonstrated that in an arbitrage-free economy, return volatility is directly related to information production - the volatility of price changes equals the rate of information flow. Under Ross's model, therefore, an increase in the rate of information flow will result in higher return volatility and vice versa.

French and Roll (1986) observed that stock returns are more volatile during trading hours than during nontrading hours and concluded that private information, in contrast to public information, is the major cause of trading volatility. Admati and Pfleiderer (1988) hypothesised a structural link between private information, trading volume and stock return volatility. In particular, both discretionary liquidity traders and informed traders will cluster, with each group preferring to trade during periods when liquidity trading volume is highest. In general, this occurs at the end of the day when Admati and Pfleiderer (1988, p.35) state that 'prices quoted at the end of the trading day will reflect more of the information that will be released publicly during the following nontrading hours.' Informed traders also have the incentive to trade on their information before the market closes. Otherwise, they face the possibility of information decay over the nontrading period if their private information becomes public.

The overnight private information hypothesis can, therefore, be summarised as follows: (i) the magnitude of return volatility reflects the flow of information; (ii) the volatility pattern observed at the end of the day reflects the information of informed traders that
will be released during the following nontrading period; (iii) the end of day ($D_t$) volatility is positively related to information production, and therefore volatility at the opening of the market the next morning ($D_{t+1}$).

Another interpretation of the higher volatility observed at the opening of the market is that it is a reflection of public overnight information released during the nontrading period. For example, Amihud and Mendelson (1991b) considered that the higher return variances at the opening of the market are a reflection of overnight public information which has accrued during the overnight nontrading period. The tendency for firms to release public information during nontrading hours has been well documented, amongst others, by Dyl and Maberly (1988), Patell and Wolfson (1982) and Penman (1987).

6.5.2 Closing Price Volatility - Risk and Speculation

The comparison of the end of day volatilities and their relationship with opening price volatility in both cash stock and futures markets is also interesting in the context of the perceived role that each market may play. Futures markets have traditionally been recognised as performing a number of economic functions including price discovery and information transfer, as well as a vehicle for hedging and insurance. Traders with market wide private information have, in addition to the decision to trade at the end of the day before closure, to decide which market to trade - the cash stock or futures market. If futures markets are transactionally more efficient, are more liquid, and are relatively easier to establish short positions; then it is argued that private information traders will prefer to establish positions in the futures markets. Further, if price volatility is a proxy for information flow then end of day futures volatility should be more highly associated with subsequent morning opening volatilities.

An alternative interpretation of higher end of day futures volatilities is that it is associated with the higher proportion of speculators in futures markets. Speculators are attracted to futures markets because of the availability of trading on leveraged margin. Further, if the information theories that suggest that traders either overreact to information, have short
term trading horizons or herd on single pieces of information are valid [DeBondt and Thaler (1989), Froot, Scharfstein and Stein (1992) and Campbell and Hentschel (1992)], then higher price volatility may be associated with factors others than information. This suggests that any observed end of day higher volatility in futures may be induced by day traders exiting the futures market. Finally, end of day volatility in futures may simply be a reflection of the higher nontrading risk associated with holding open positions in futures.

To summarise, a number of researchers have hypothesised that the opening spikes in volatility are associated with public or private information but little research has attempted to delineate the relative importance of each information set. The objective of this section is to determine the relative impact of private information compared to public information on the subsequent mornings opening price volatility. By filtering out the impact of information on volatility then the effects of trading structures or other factors may be more easily isolated. These research questions are now empirically considered.

6.5.3 Description of the Model

The first research problem was to determine the relative association between private and public information and the information set generated at the opening of the AOI stock and SPI futures market. As a proxy for volatility and the information set, the squared returns from each series (DJ65, AOI and SPI) were calculated [per Chan, Chan and Karolyi (1991), Jain and Joh (1988), Clark (1973) and Karpoff (1987)\(^8\)]. The squared returns on the DJ65 from the previous day were then used as a proxy for public overnight information and the squared returns from the previous days close on the AOI or SPI were used as a proxy for private information.\(^9\)

---

\(^8\) Karpoff (1987) provides a review.

\(^9\) This method has some similarities with the ARCH and GARCH models developed by Engle (1982) and Bollerslev (1986). The transfer function method used in this chapter has the additional flexibility of being able to estimate different functional forms.
The statistical technique used was the transfer function time series model outlined and discussed in chapter four. The following model was applied to the AOI and SPI squared return series ($\eta^2_t$):

$$
\eta^2_t = \alpha + \sum_{i=1}^{q} \Psi^i \eta^2_{t-i} + \sum_{j=1}^{n} \delta^j X^j + \nu(B) I_t + \nu(B) \eta^2_{c(t-1)} + \epsilon_t 
$$

(6.3)

where

- $\alpha$ is the intercept term;
- $\sum_{i=1}^{q} \Psi^i \eta^2_{t-i}$ represents the autoregressive time series effects from previous volatility;
- $\sum_{j=1}^{n} \delta^j X^j$ represents the significant spikes in intraday volatility;
- $\nu(B) I_t$ represents the impact of an input variable ($I_t$) on $\eta^2_t$;
- $\nu(B) \eta^2_{c(t-1)}$ is the pulse transfer of volatility from the previous days close on the following days opening and subsequent volatility; and
- $\epsilon_t$ is the residual term.

The above model fulfills a number of objectives. Firstly, by estimating the autoregressive components the model is purged of any dynamic effects which potentially explain current volatility. These coefficients represent a raw measure of the persistence of the volatility in the SPI and AOI markets. They may be a proxy for a slow release of private information or patterns induced by the information theories of DeBondt and Thaler (1989) and Froot, Scharfstein and Stein (1992).

Secondly, the previous day’s squared return on the DJ65 is an input variable into equation (6.3) as it is hypothesised to proxy for public information. This is accounted for through the intervention ($I_t = DJ65_t$) which is zero for $t < 1000$ in the stock market (0950 in futures) and $\nu(B)$ taking some functional form to be identified from the data for $t \geq 1000$ in the stock market (0950 in futures). The intervention and transfer function
estimate the association between the previous overnight volatility intervention from the DJ65, and whether there are any further 'spillovers' into subsequent volatility.

Thirdly, the impulse function $u(B)\eta^2_{c(t-1)}$ estimates the impact that the previous nights excess\textsuperscript{10} closing volatility has on the next mornings opening volatility. If excess closing volatility is a proxy for private information then there should be a positive association between closing and subsequent volatilities. If there is no association or a negative relationship then this indicates that excess closing volatility may be induced by factors other than information.

Finally, the fixed term determines if the remaining volatility (after purging the dynamic and information effects) at specified times of the day is significantly higher or lower than the other remaining time of the day volatilities. This may give an indication as to whether the remaining volatility is induced by microstructural effects such as opening price setting procedures. In this manner the volatility at the opening time (0950) can be decomposed and related to the separate dynamic components, the fixed component, and those proportions related to the previous nights closing volatility and the volatility induced by the DJ65.

Consistent with the statistical methodology described in chapter four for the Box-Jenkins model formulation (identification) techniques both for autoregressive integrated moving average (ARIMA) and transfer function models, and introducing appropriate interventions to account for significant spikes or jumps in the volatility series, an appropriate model was determined in three stages. The first stage was to run a straight forward autoregressive time series model with dummy variables to establish whether there were any significantly higher time of the day volatilities. The next stage was to build up the model by adding a pulse function from the previous day's closing volatility. The statistical output was then analysed to establish whether this addition was a

\textsuperscript{10}Excess volatility is volatility greater than the adjusted intraday mean volatility. It could be argued that using excess volatility at close and raw volatility from the overnight DJ65 biases the analysis in favour of the overnight public information hypothesis. All the tests in this section were rerun using raw unadjusted closing volatility as a proxy for private information but there was no change in the conclusions.
significant improvement to the explanatory power. Finally, the intervention from the
overnight US volatility along with any transfer function was estimated. In this way the
separate impacts from the previous day’s release of private information and the overnight
public information together with any volatility spillover effects were estimated.

6.5.4 Empirical Results - AOI Volatility

The autoregressive and fixed time of the day model for the volatility of the AOI was
estimated as follows:

\[ \eta_t^2 = \alpha + \psi_1 \eta_{t-1}^2 + \psi_2 \eta_{t-2}^2 + \psi_3 \eta_{t-4}^2 + \psi_4 \eta_{t-20}^2 + \delta_1 X_{1t} + \delta_2 X_{2t} \\
+ \delta_3 X_{3t} + \delta_4 X_{4t} \]

where \( \alpha \) is the intercept term, the \( \eta_{t-j} \), \( j = 1, 2, 4, 20 \) represent the autoregressive
components of the model with the fixed time of the day indicator dummy variables taking
the values:

\[
X_{1t} = 1, t = 1000, \quad \text{otherwise} = 0. \\
X_{2t} = 1, t = 1015, \quad \text{otherwise} = 0. \\
X_{3t} = 1, t = 1030, \quad \text{otherwise} = 0. \\
X_{4t} = 1, t = 1600, \quad \text{otherwise} = 0.
\]

and \( \psi_j \) (\( j = 1,\ldots,4 \)), \( \delta_j \) (\( j = 1,\ldots,4 \)) are parameters to be estimated. The estimated
coefficients together with their associated t-ratios are listed in Table 6.5.

The initial model indicates that there is some persistence in the volatility of the AOI with
the lags at 1, 2, 4, and 20 statistically significant. The highest influence on current
volatility was the level of volatility at the same time on the previous day (\( \psi_4=0.105 \)),
followed by the previous period volatility (\( \psi_1=0.054 \)). The fixed time of the day dummy
coefficients confirm that the volatility at the opening is the highest of the day and that the
volatility at 1015 and 1030 is significantly higher than the remainder of the day. The
closing volatility was not significantly different from the mean interior volatilities. The above model was extended by adding the pulse transfer function on the previous nights excess closing volatility (as a proxy for private information) to observe if there was any association with the next mornings opening volatility.

### Table 6.5

**AOI Intraday Volatility - Time Series and Time of the Day**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>T-Ratio</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( \alpha )</td>
<td>0.0087</td>
<td>3.84</td>
</tr>
<tr>
<td>2</td>
<td>( \psi_1 )</td>
<td>0.0538</td>
<td>3.82</td>
</tr>
<tr>
<td>3</td>
<td>( \psi_2 )</td>
<td>0.0347</td>
<td>2.46</td>
</tr>
<tr>
<td>4</td>
<td>( \psi_3 )</td>
<td>0.0313</td>
<td>2.23</td>
</tr>
<tr>
<td>5</td>
<td>( \psi_4 )</td>
<td>0.1045</td>
<td>7.44</td>
</tr>
<tr>
<td>6</td>
<td>( \delta_1 )</td>
<td>0.1517</td>
<td>18.32</td>
</tr>
<tr>
<td>7</td>
<td>( \delta_2 )</td>
<td>0.0322</td>
<td>3.90</td>
</tr>
<tr>
<td>8</td>
<td>( \delta_3 )</td>
<td>0.0164</td>
<td>1.99</td>
</tr>
<tr>
<td>9</td>
<td>( \delta_4 )</td>
<td>0.0021</td>
<td>0.25</td>
</tr>
</tbody>
</table>

| Residual Variance | 0.012879 | Schwartz BC | -7501.86 |
| Standard Error (RV) | 0.113487 | Akaike IC   | -7560.51 |

An inspection of the output from this model showed that the pulse transfer function coefficient was small and positive but not significant. Further, whilst the residual variance was marginally lower, the Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC) showed a marginal reduction in the information criterion added to the equation from the previous nights closing AOI volatility. Furthermore, the volatilities at 1000 and 1015 were little changed. This was in contrast to the further addition of the DJ65 volatility which resulted in significantly improved information criteria, improved residual variance and lower fixed time of the day volatilities at 1000 and 1015. The final model which incorporated both public and private information was estimated as follows:

\[
\eta^2_t = \alpha + \psi_1 \eta^2_{t-1} + \psi_2 \eta^2_{t-2} + \psi_3 \eta^2_{t-4} + \psi_4 \eta^2_{t-20} + \delta_1 X_{1t} + \\
[(\gamma/(1 - \beta_1B))] DJ65^2_t + \delta_2 X_{2t} + \delta_3 X_{3t} + [(\delta_4)/(1 - \omega^2B^2)] X_{4t}
\]
The residual variance from the full model was reduced and both information criteria improved. The Ljung-Box chi-square statistic showed that there was no significant autocorrelation in the residuals and the other standard tests indicated that they were normally distributed. The detailed output from this model is reported in Table 6.6 and implies the following:

(i) The coefficient on the DJ65 volatility is positive and significant and the transfer function denominator is significant to lag one. This means that about 15% of the overnight volatility on the DJ65 composite index is reflected into the opening volatility (at 1000) of the AOI and 17% of this volatility subsequently impacts across into the subsequent AOI volatility at 1015. This in turn accounts for 43% of the excess volatility at 1000 ($\delta_1$ reduced from 0.1516 to 0.0866), and 41% of the excess volatility at 1015 ($\delta_2$ reduced from 0.0322 to 0.0191) from that previously determined by the simple autoregressive and fixed time of the day model.

(ii) The impulse transfer function applied to the previous nights excess closing volatility on the AOI (at 1600) was not significant. Taken together with the results of the previous model this suggests that private information does not add any explanatory power to the subsequent opening volatility over and above the information contained in the public information from the overnight volatility of the DJ65.

(iii) After accounting for any potential private and public information impacts, the volatilities at the 1000 opening, 1015 and 1030 are significantly higher, at the 10% level, than the volatilities observed for the remainder of the day. These may be related to the structure of the market (especially the opening volatility) and this proposition is examined further by analysing the impact of private and public information on the opening futures volatility.
Table 6.6
AOI Intraday Volatility - The Impact of Public and Private Information

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>T-Ratio</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>α</td>
<td>0.0080</td>
<td>2.69</td>
</tr>
<tr>
<td>2</td>
<td>Ψ1</td>
<td>0.0494</td>
<td>3.51</td>
</tr>
<tr>
<td>3</td>
<td>Ψ2</td>
<td>0.0361</td>
<td>2.56</td>
</tr>
<tr>
<td>4</td>
<td>Ψ3</td>
<td>0.0322</td>
<td>2.28</td>
</tr>
<tr>
<td>5</td>
<td>Ψ4</td>
<td>0.1112</td>
<td>7.90</td>
</tr>
<tr>
<td>6</td>
<td>δ1</td>
<td>0.0866</td>
<td>9.11</td>
</tr>
<tr>
<td>7</td>
<td>γ</td>
<td>0.1514</td>
<td>14.62</td>
</tr>
<tr>
<td>8</td>
<td>β1</td>
<td>0.1684</td>
<td>2.55</td>
</tr>
<tr>
<td>9</td>
<td>δ2</td>
<td>0.0191</td>
<td>1.91</td>
</tr>
<tr>
<td>10</td>
<td>δ3</td>
<td>0.0150</td>
<td>1.77</td>
</tr>
<tr>
<td>11</td>
<td>δ4</td>
<td>0.0034</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Residual Variance | 0.012399 | Schwartz BC |
Standard Error (RV) | 0.111351 | Akaike IC |

-7714.87
-7636.72

6.5.5 Empirical Results - SPI Volatility

The autoregressive and fixed time of the day model for the volatility of the SPI was estimated as follows:

$$\eta_{t}^{2} = \alpha + \psi_1 \eta_{t-1}^{2} + \psi_2 \eta_{t-2}^{2} + \psi_3 \eta_{t-3}^{2} + \psi_4 \eta_{t-5}^{2} + \psi_5 \eta_{t-8}^{2} + \psi_6 \eta_{t-11}^{2} + \psi_7 \eta_{t-20}^{2} + \psi_8 \eta_{t-21}^{2} + \psi_9 \eta_{t-38}^{2} + \psi_{10} \eta_{t-39}^{2} + \delta_1 X_{1t} + \delta_2 X_{2t} + \delta_3 X_{3t} + \delta_4 X_{4t} + \delta_5 X_{5t}$$

where the $\eta_{t-j}^{2}$, $j = 1, 2, 3, 5, 8, 11, 20, 21, 38, 39$ represent the autoregressive components of the model with the fixed time of the day indicator dummy variables taking the values:

- $X_{1t} = 1, t = 950, \text{ otherwise } 0.$
- $X_{2t} = 1, t = 1000, \text{ otherwise } 0.$
- $X_{3t} = 1, t = 1015, \text{ otherwise } 0.$
- $X_{4t} = 1, t = 1030, \text{ otherwise } 0.$
- $X_{5t} = 1, t = 1610, \text{ otherwise } 0.$

and $\psi_{j}$ ($j = 1, \ldots, 39$), $\delta_{j}$ ($j = 1, \ldots, 5$) are parameters to be estimated. The estimated coefficients together with their associated t-ratios are listed in Table 6.7.
The initial model indicates that there was a high level of persistence in the volatility of the SPI with various volatilities up to lag 39 significant. The largest autoregressive parameter was at lag 2 with the size of the parameters declining only slightly over time. When compared to the AOI, it was apparent that the SPI had a greater persistence in volatility. In other words the past volatility had a longer and more persistent impact on current volatility. The fixed time of the day dummy coefficients confirmed that the volatility at the opening (0950) was the highest of the day and together with the volatilities at 1000, 1015 and 1030 was significantly higher at the 5% level than the remainder of the day. The closing volatility at 1610 was higher than the interior volatilities but was not statistically significant. The model was extended by adding the pulse transfer function on the previous nights SPI closing volatility and the results indicated that there was no significant relation between the previous nights closing volatility on the SPI and subsequent opening volatilities. Similar to the AOI the residual variance of the extended model was only slightly reduced, the Akaike Information Criterion (-7028.88) and the Schwartz Bayesian Criterion were both increased (-6916.48) indicating an inferior model.
Next, the model was further extended by adding the overnight volatility from the DJ65. The estimated final model is reported below in Table 6.8 along with the associated estimates and t-ratios.

\[ \eta^2_t = \alpha + \psi_1 \eta^2_{t-1} + \psi_2 \eta^2_{t-2} + \psi_3 \eta^2_{t-3} + \psi_4 \eta^2_{t-5} + \psi_5 \eta^2_{t-8} + \psi_6 \eta^2_{t-11} + \psi_7 \eta^2_{t-20} + \psi_8 \eta^2_{t-22} + \psi_9 \eta^2_{t-23} + \psi_{10} \eta^2_{t-38} + \psi_{11} \eta^2_{t-39} + \delta_1 X_{1t} + \gamma DJ65^2_{t} + \delta_3 X_{3t} + \delta_4 X_{4t} + [(\delta_5)/(1 - \omega^2 B^2)] X_{5t} \]

**Table 6.8**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>T-Ratio</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( \alpha )</td>
<td>0.0025</td>
<td>11.37</td>
</tr>
<tr>
<td>2</td>
<td>( \Psi_1 )</td>
<td>0.0496</td>
<td>3.68</td>
</tr>
<tr>
<td>3</td>
<td>( \Psi_2 )</td>
<td>0.0584</td>
<td>4.33</td>
</tr>
<tr>
<td>4</td>
<td>( \Psi_3 )</td>
<td>0.0627</td>
<td>4.65</td>
</tr>
<tr>
<td>5</td>
<td>( \Psi_4 )</td>
<td>0.0327</td>
<td>2.42</td>
</tr>
<tr>
<td>6</td>
<td>( \Psi_5 )</td>
<td>0.0399</td>
<td>2.96</td>
</tr>
<tr>
<td>7</td>
<td>( \Psi_6 )</td>
<td>0.0309</td>
<td>2.30</td>
</tr>
<tr>
<td>8</td>
<td>( \Psi_7 )</td>
<td>0.0418</td>
<td>3.11</td>
</tr>
<tr>
<td>9</td>
<td>( \Psi_8 )</td>
<td>0.0322</td>
<td>2.40</td>
</tr>
<tr>
<td>10</td>
<td>( \Psi_9 )</td>
<td>-0.0534</td>
<td>-3.97</td>
</tr>
<tr>
<td>11</td>
<td>( \Psi_{10} )</td>
<td>0.0372</td>
<td>2.77</td>
</tr>
<tr>
<td>12</td>
<td>( \Psi_{11} )</td>
<td>0.0331</td>
<td>2.47</td>
</tr>
<tr>
<td>13</td>
<td>( \delta_1 )</td>
<td>0.1393</td>
<td>13.86</td>
</tr>
<tr>
<td>14</td>
<td>( \gamma )</td>
<td>0.3538</td>
<td>33.36</td>
</tr>
<tr>
<td>15</td>
<td>( \delta_3 )</td>
<td>0.0256</td>
<td>3.61</td>
</tr>
<tr>
<td>16</td>
<td>( \delta_4 )</td>
<td>0.0218</td>
<td>2.78</td>
</tr>
<tr>
<td>17</td>
<td>( \delta_5 )</td>
<td>0.0059</td>
<td>1.23</td>
</tr>
<tr>
<td>18</td>
<td>( \omega_2 )</td>
<td>-0.8279</td>
<td>-3.24</td>
</tr>
</tbody>
</table>

The residual variance from the full model was reduced by 16.3% and both information criteria measures indicated an improved model when compared to the simple model (Table 6.7). The Ljung-Box chi-square statistic and standard residual analysis showed that there was no significant autocorrelation in the residuals and that they were normally distributed. This indicates that the full model is statistically superior to the two previous models and implies the following:
(i) The overnight volatility on the DJ65 composite index, as a proxy for public information, has a relatively larger impact on the opening volatility of the SPI (0.354) compared to the AOI (0.151) but the impact is restricted to 0950 prices with no volatility transfer across into subsequent prices.

(ii) The denominator of the pulse function on the previous nights closing volatility at 1610, as a proxy for private information, is negative (-0.828) and significant across two lags. This means that the excess volatility at the close of trading on the previous night has a negative relationship with the volatilities at 0950 and 1000 on the subsequent morning. This result is opposite to the private information hypothesis which predicts that there would be a positive relationship and suggests that the volatility at the close of the Australian futures market may be related to factors other than private information.

(iii) A major cause of volatility during the early morning trading period in the SPI, therefore, appears to be related to the arrival of public information in the form of the overnight volatility on the DJ65. This accounts for approximately 57% of the excess volatility at 0950 (δ1 reduced from 0.2735 to 0.1175), and all of the excess volatility at 1000 (δ2 reduced from 0.0178 to zero), when compared to the simple autoregressive and fixed time of the day model.

(iv) Other points to note are the closing volatility in the SPI was not significantly higher than the interior volatilities and the previous day's volatility (t-22) has a negative relationship with current volatility.

6.6 SUMMARY AND CONCLUSIONS

This chapter examined the trading, nontrading and intraday volatility of the AOI and SPI. The purpose of the analysis was to compare and contrast the microstructure volatility in Australia with previous research in the US; to compare the contemporaneous volatility in the stock market with the futures market; and to analyse the impact of private and public information on opening volatility.
The interday variance ratio methodology of Amihud and Mendelson (1987) was used to examine the impact of price setting structures on opening prices in section. The open to close ratio in the futures market was 1.067 and in the stock market was 1.018. This initial result suggests that opening the market with a continuous open outcry mechanism will increase the volatility of prices. However, the 1015-to-close variance ratio in the AOI was 1.185 (similar to the open-to-close variance ratios observed in the US and Japan) and suggests that the opening price setting mechanism for stocks in Australia does not dampen volatility but only serves to postpone volatility to the following period. These results support the conclusions that the choice of opening price setting mechanisms will have an impact on opening volatility, and that the open outcry system utilised in the futures market does not induce excessive volatility compared to stock market procedures.

The trading and nontrading analysis of French and Roll (1986) applied to the data found that there is significantly greater intensity of volatility during trading hours compared to nontrading hours. Further, the ratio of trading to nontrading volatility in futures was some 26% higher than the stock market and the trading time volatility was higher and more persistent in the futures market. It was also observed that the resumption of futures trading after lunch was associated with an increase in volatility in both markets.

The study of volatility was then extended to an intraday analysis using 15-minute observations. An L-shaped pattern in intraday volatility was found with the opening volatility in both markets significantly higher than interior volatilities. The closing volatility showed a small upkick but it was not of the same magnitude observed in the US. The lower closing volatility in Australia may be associated with different trading structures. The SPI was computer traded after hours from 1645 to 0400 during the period of the study and this may have reduced the overnight risk as investors could enter and exit the market as overnight information emerged.

The unadjusted intraday volatility in the futures market was consistently higher than the stock market. One potential explanation was the thin trading in the Australian stock market which dampens the observed intraday volatility. This factor was accounted for by
comparing the futures volatility to the liquid TLI index and by making an adjustment, suggested by Merton, directly to the AOI. Depending on the measure of stock market volatility the thin trading feature explained between 23% to 49% of the difference in volatility. The remaining higher volatility in the SPI could be related to the arrival of private information or to speculative activity.

The relative impact of private and public information as a cause of the high opening and persistent volatility was then examined. The impulse function fitted to the previous nights closing volatility had very little explanatory power for the opening AOI volatilities. For the SPI the relationship was negative and indicates that the closing volatility in the futures market is not related to expected volatility (or private information). On the other hand, overnight public information modelled as an intervention and transfer function on the previous days DJ65 volatility had significant explanatory power for opening volatility. Public information has a relatively larger impact on the futures market opening volatility and explains more of the opening volatility spikes. The autoregressive time series model fitted to the volatilities revealed that the futures market had a longer and more persistent volatility memory which lasted almost two days.

The above empirical observations can be more briefly summarised as follows. The structure of the opening price setting mechanism has implications for price volatility. Futures markets have consistently higher volatility and have more persistent volatility patterns. Volatility persistence may be related to the release of private information but this is an unlikely explanation seeing that the lag pattern is almost two days old. The higher futures volatility is only partly explained by thin trading in the component stocks of the AOI. The closing volatility in the SPI is not related to potential overnight information release and the SPI futures reacts more to public information. Taken together the evidence suggests that a component of short term futures price volatility may be induced by superior information gathering ability or speculative elements.

The next chapter analyses whether the impact of derivative futures trading and the higher short term volatility in futures is transferred into a higher longer term volatility in the
underlying stock market. Any evidence of a significant increase in long term cash volatility may be construed as evidence that speculative activity in the futures has permanently 'spilled over' into the stock market. Conversely, no change or a lower volatility suggests that the effects of speculative higher short term volatility are short lived or are a proxy for information transfer.
Figure 6.2 Intraday volatility of the AOI and SPI

* Volatilities multiplied by $10^{0.2}$
CHAPTER SEVEN

THE LONG RUN IMPACT OF INDEX FUTURES MARKETS ON
STOCK MARKET VOLATILITY

7.1 INTRODUCTION

Whenever the stock market goes through a period of high volatility, which has been the case during the 1980's [Kearns and Pagan (1990)], some market analysts attempt to explain the complex causes of market volatility by seeking out a simple solution. This period was also associated with a dramatic increase in the number of derivative securities traded on the Sydney futures exchange [see Table 1.1]. Among these are futures and futures option contracts written on the AOI. The introduction of these index derivatives has allowed arbitrage strategies to be traded between spot shares and the futures markets - a natural extension being program trading - and the availability of a wide range of both insurance and speculative strategies.

This raises important questions about the effect that index derivatives have on the volatility of the cash stock market. One view is that the higher volatility in futures markets, caused by more highly levered and speculative participants, may be a major contributing factor in increasing the volatility of the spot [see Brady (1988), Edwards (1988b), Cagan (1981)]. Based upon the casual observation that the introduction of

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1 A substantial part of this chapter has been published in the Journal of Business Finance and Accounting, 18(2), January 1991, (Hodgson, A. and Nicholls D.), pp.267-280, jointly with my thesis supervisor, Dr. D. Nicholls.
derivative futures trading coincided with recent stock market volatility, it is not surprising that indices of futures and their options have been singled out as one of the more likely causes of sharemarket volatility and even the October 1987 stock market crash. For example, concern about index futures and their effect on US stock market volatility predates the October 1987 crash. Edwards, (1988b), and Martin and Senchack (1989) quote a survey conducted for the National Association of Securities Dealers where almost 60% of investors blamed the increase in US stock market risk after the 1987 crash on stock index futures and options trading. In Australia an article in the Financial Review of 8 October, 1987 entitled, 'Forget Wall St: Futures are key to market's problems', cites the concern by a number of observers that the cause of stock market volatility was the dangerously volatile Australian futures market, which was controlled by smaller speculators and 'day traders'. In very recent times the futures trading by Barings Merchant Bank in the Nikkei 225 futures index has been blamed for a 4% drop in the Nikkei stock index on 28 February 1995.2

The question of whether trading in derivative securities increases the volatility of spot equity markets is of practical importance, because it could have repercussions in a number of critical areas in the economy. Increased market volatility may increase real interest rates3 and the cost of capital4, leading to a reduction in the value of investments

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3 Interest rates may be increased and become more variable; if futures market speculation absorbs credit away from productive uses in the economy, and price volatility increases the possibility of default on margin loans [see Cagan (1981), Brady (1988)].
4 Using the capital asset pricing model the cost of equity capital can be written as [Sharpe (1970, Chapter 5)]:

\[
\frac{-R_i}{R_f} = \frac{(R_m - R_f)}{\sigma_m} \tau_{im} \sigma_i
\]

where \(R_i\) is the cost of equity capital, \(R_f\) is the risk free interest rate, \(\sigma_{im}\) is the volatility of the market portfolio, and \(\sigma_i\) is the volatility of the stock market index, which is a subset of the market portfolio. \([R_m - R_f] / \sigma_m\) is the market price of risk, and \(\tau_{im} \sigma_i\) is the relative measure of risk contributed by the stock market index. If we assume that the stock market represents only a small proportion of the total market portfolio, then if \(\sigma_i\) increases, this translates directly into an increase in the cost of share equity capital. If, however, the stock market is a large proportion of the market portfolio then an increase in the volatility of stock markets will have secondary effects which are dependent on society's risk aversion preferences and the marginal production of the economy's productive endowment.
and loss of confidence in the stock market.\(^5\) In turn this can lead to a flow of capital away from equity markets. Secondly, with increased volatility regulatory bodies may interfere in markets to enact further regulation or exclude certain securities\(^6\), with potential detriment to allocational efficiency. Stein (1987, p. 1124) expresses this view as follows:

'One of the most important implications of the stabilizing/destabilizing debate concerns the desirability of opening futures or options markets. Regulators have frequently expressed concern that futures and option markets can be price destabilizing and welfare reducing.'

Another view is that derivative futures markets reduce spot volatility by providing low cost state-contingent strategies which enable investors to minimise portfolio risk, by introducing positive information externalities and by transferring speculators from spot markets to futures markets. Futures have a stabilising influence. It is also of note that increased spot volatility from futures markets may not be undesirable if induced by objective new information. In general, the quicker and more accurate prices reflect new information the more efficient should be the allocation of resources. Only price volatility greater than that justified by fundamental economic conditions is undesirable, by definition.

In Australia, index futures began trading in February 1983 and index futures options in June 1985. As a result, there exists a substantial database on which to test any contention regarding futures markets and changes in volatility of the underlying cash equity market. This chapter offers some empirical evidence on this research problem.

The plan is as follows. Some advantages and disadvantages of index derivative security

---

\(^5\) A loss in confidence may also occur if unwarranted excess volatility increases the cost (and decreases) the use of insurance strategies (eg. through using put options).

\(^6\) For example by increasing margins, implementing pricing limits and trading halts, or by demanding settlement in shares rather than cash. In the US, Security and Exchange Commission regulations impose a limit on the number of traded stock index option contracts that can be held by institutional investors, the introduction of trading in futures contracts has been delayed (interest rates futures) or closed down (onion futures). These procedures reduce the transaction and leverage advantage that derivatives enjoy over cash markets.
markets are outlined in section 7.2. The theoretical debate on how cash stock market volatility might be increased, together with the results of previous empirical research, is reviewed in section 7.3. The research design adopted is discussed in section 7.4 and the results of the application of this procedure and the conclusion reached are presented in sections 7.5 and 7.6 respectively.

7.2 ADVANTAGES AND DISADVANTAGES OF INDEX DERIVATIVES

Index futures contracts have a transaction cost advantage over the direct purchase of equities and forward contracts and they reduce search, liquidity, moral hazard and brokerage costs [Cagan (1981), Jaffe (1984) and Veljanovski (1986)]. This allows managers and other investors to either diversify or increase market risk easily and at low cost [Figlewski and Kon (1982)]. Trading can also be initiated in index futures contracts by posting only an initial margin; thus enabling investors to trade on accessible credit. Margins vary as a percentage of the contract, but in general are less than 5%. Whilst positions are also marked to market on a daily basis, the net effect (except for extreme changes) is an advantage for traders over arranging credit for direct leverage purposes [Jaffe (1984)].

Index futures option contracts add additional benefits. They provide a transactionally efficient means to further rebundle ex ante rights and obligations. This enables holders to alter and extend future payoff patterns by extending hedging and trading strategies over those offered by futures contracts. Further, they provide liquidity advantages over direct options and information on expected futures market volatility [Brace and Hodgson (1991)]. Futures and futures option markets therefore provide unique information in addition to that provided by spot markets; and the varied patterns of risk and return available in futures markets cannot be efficiently duplicated in spot option or equity markets. Theoretically, because of these economic benefits, it is desirable that both futures and futures option markets be developed and maintained on the share price index.
In practice, however, these benefits may be outweighed by an increase in unwarranted stock market volatility (considered below) and other disadvantages. For example, if arbitrage strategies are common then share prices may become divorced from underlying fundamentals and become more closely related to each other and to futures prices [Martin and Senchack (1989)]. Scarce funds may be absorbed by margined futures speculators away from productive activities increasing the possibility of default on margin loans and affecting the conduct of monetary policy [Cagan (1981)], and lead to the over valuation of shares and increase the potential for a precipitate price decline [Brady (1988)]. In these cases the social value of derivative futures may be negative.

7.3 VOLATILITY IN CASH STOCK MARKETS

There are two basic mechanisms whereby the volatility of the cash stock market might be increased. The first is indirectly through speculation. The second is directly through arbitrage strategies, such as trading the cost of carry relationship or computer trading, or through portfolio insurance techniques.

One common claim is that derivative securities increase the volatility of cash markets by speculation in the overlying markets. Speculation which increases price variability - not in a beneficial sense by reflecting the underlying volatility of actual economic conditions - but in the undesirable sense that if speculation were constrained, then the volatility of cash prices would be less without adversely affecting the allocation of resources. Public opinion often seems to parallel long held quasi-religious condemnations of 'money changers' and unproductive economic activities - only agriculture and some manufacturing appear to be excepted [Cagan (1981, p. 10)]. Judged by comments like: 'Part of the sharemarket's Australian-ness is its volatility', and 'Given that our sharemarket has fallen more than most others, the quick failure in Australia has confirmed what the world appears to believe: that Australian shares were driven speculatively', [Business Review Weekly (1987), and (1988)]. Opinion in Australia appears to be that the physical stock market is driven by speculative elements.
From a theoretical economic viewpoint, if speculation were to move prices away from levels consistent with future developments and to produce movements that increased the variability of prices, the speculators responsible would, on average, incur losses as other more efficient speculators would buy low and sell high. These losses would gradually reduce the number of inefficient speculators; as the reduction process proceeded the unstable speculation would disappear [Friedman (1953)]. A number of theoretical papers have investigated similar hypotheses in derivative and futures markets. They argue that the introduction of derivative securities, such as futures markets, always lowers the mean and variance of spot price movements [Peck (1976), Turnovsky (1979), Campbell and Turnovsky (1982)], because of the informational role these markets provide. They become a centralised clearing house for information, collecting, analysing and disseminating the collective beliefs of all market traders. This activity also provides an externality for cash market participants, who can base their current hedging and purchase decisions on this extra information. That leads to intertemporal smoother and more efficient resource usage [Powers (1970), Cox (1976)]. As a consequence, cash prices become more sensitive and responsive to actual market conditions. Any observed increase in price volatility is the result of a more efficient market induced by futures price mapping and is desirable for intertemporal decision making.

There are other reasons to believe that futures markets might reduce the volatility of cash markets. Risk taking speculators are attracted to futures by the low margins, low transaction costs and the standardised contracts and trading conditions. Therefore, the presence of futures may transfer speculative activity away from the cash market and into futures and thereby reducing cash volatility. Investors are now not forced to fine tune market risk by buying and selling in cash markets. Trading, and hence volatility, can be isolated to the index futures markets. Also, by providing investors with hedging protection, futures contracts help to immunise their portfolios against systematic risk. Grossman [1988], argues that the prices of futures securities convey important information about the costs of insurance strategies. If futures and options trading is restricted, then large institutional managers will be forced to use synthetic strategies (by
combining cash securities) to insure holdings. Hence, portfolio insurers will not know the cost of these strategies when they do not know the intensity with which other investors are using similar strategies. If a substantial number of investors suddenly decide to use synthetic insurance strategies predicated on historical stock market volatility, then this will raise cash stock market and index futures price volatility.

There are however counterarguments to the above. Destabilising price movements might occur if they are produced by amateur speculators who lose money, retire, and are continually replaced by others equally inept [Kaldor (1939)]. Thus in speculative markets, the retort to the argument that traders cannot be continually fooled, is that it is achieved with a continuous turnover of naive speculators. Further, Baumol (1957), hypothesises that speculators buy or sell only after a price movement has started, which accelerates price trends and causes prices to be more volatile. If speculation tends to increase price variability and futures markets are a signalling device to cash markets, derivative futures markets, which make speculative trading inexpensive through low margin costs, would thus help to increase the variability of cash markets.

Futures speculators may also bring a negative information externality to participants already operating in cash markets. If secondary futures traders have a noisy observation of the effects of permanent shocks to prices then they may bring about a destabilising equilibrium. If cash traders can predict the actions of secondary traders, the market is riskless to cash traders and they will arbitrage away any potential profits. However, if the actions of secondary futures traders are unpredictable, the increase in perceived risk makes risk averse cash traders back out of the market somewhat, leaving behind imperfectly stabilised prices. The net result can be one of price destabilisation and welfare reduction [Stein, (1987, p. 142)].

The second way that volatility may be transferred from derivative markets to cash markets is via program trading and portfolio insurance techniques. This is made possible by the interconnection between stock markets, index futures and index futures options markets. They are linked by instruments, participants, trading strategies and resource
flows. For example, index futures and cash stock markets are directly linked by a cost-of-carry relationship and by cash/futures arbitrage arising from that relationship [see Bowers and Twite (1985), Hanan and Harpaz (1986)]. Program trading is a trading technique designed to exploit misalignments from the cost-of-carry relationship by simultaneously buying in one market and selling in the other. Another link is the use of derivatives by institutions to protect a portfolio of shares from a loss in value. Participants in these markets routinely hedge their positions by using options to hedge futures, futures and options to hedge cash positions, and so on. Finally, options and futures are also used as a fast and low-cost means to enter and exit the physical stock market.

All of the above strategies, to some extent, also rely on computer analysis of prices and computer market making and tend to be more active during large and/or volatile price movements. Because the computer automatically implements or signals trading, a number of market observers have alleged that these techniques directly transfer the higher volatility in futures markets into the underlying cash market [see Finnerty and Park, 1987]. Further, because it is assumed that derivative markets can be relatively non-liquid, futures markets cannot absorb abnormal buying or selling pressure without dramatic price fluctuations. In commenting on the October 1987 stock market crash, the Report of the Presidential Task Force on Market Mechanisms comments as follows:

>'The futures market simply could not absorb such selling pressure without dramatic price declines. Moreover, reflecting the natural linkages among markets, the selling pressure washed across to the stock market, both through index arbitrage and direct portfolio insurance stock sales.' [Brady (1988, p56)]

Empirical evidence is mixed. In commodity futures, a number of papers have found a reduction in cash prices after the introduction of futures trading in onions [Working (1960), Gray (1963), Johnson (1973)], and live cattle [Powers (1970), Taylor and Leuthold (1974)]. The reduction was mainly attributed to the increase in speed and area of saturation with which futures markets disseminate information. Other research found
that, in the majority of cases, futures markets do not cause changes in spot price variability [Rutledge (1986), Grammatikos and Saunders (1986)].

In financial futures, most of the evidence on US Government National Mortgage Association (GNMA) securities concludes that futures trading is not a destabilising factor in cash markets [Froewiss (1978), Simpson and Ireland (1982), Moriarity and Tosini (1985), Bhattacharya, Ranjee and Ranjee (1986)]. Figlewski (1981), however, concluded that a class of futures investors, acting on imperfect information, increased cash volatility. In index futures, there is evidence that the long term volatility of the Standard & Poors cash index was greater before futures trading [Edwards (1988)]. In contrast, other research shows an increase in short term spot volatility when index futures, options and index futures options expire [Stoll and Whaley (1987)], and a significant relation between a change in index futures prices and subsequent cash prices [Finnerty and Park (1987)]. Finally, two other papers have found a reduction in the volatility of share prices after trading in their options began [Nabor and Park (1988), Gemmill (1988)].

The above discussion both supports and refutes the proposition that futures markets will destabilise cash prices. Further, a priori, the economic and social costs of short-term and infrequent periods of excess or undesirable volatility are minimal when compared to sustained long-term effects. The key research issue, then, is whether futures trading cause any long run change increase in volatility and leads into the formulation of the testable hypothesis below.

7.4 RESEARCH DESIGN

7.4.1 Hypothesis Formulation

Any tests applied to measure the effects of an intervention (such as the introduction of futures option trading) on the cash stock index will require knowledge of when the intervention took place, followed by an analysis of the behaviour of the spot share index
before and after the event. The interventions (and their effects, if any, on the spot share index) which will be investigated here are:

(i) the introduction of index futures from 17 February 1983;
(ii) the introduction of index futures options from 18 June 1985.

Taking the above into account the hypothesis to be examined is:

H(1): The introduction of trading in index futures and index futures options in Australia has not affected the long term volatility of the underlying spot sharemarket

which can be simply labelled as a non-destabilising hypothesis.

At this point it should also be noted that there are a number of difficulties in designing tests to settle this research question. As with similar previous research the analysis is a joint test of no change in volatility and no intervening effects. The tests applied will involve a longitudinal study of the underlying stock index, by first identifying an intervention and then analysing the behaviour of the cash stock index before and after that intervention. But stock markets are affected by a number of events over a period of time, so there is a problem of confounding or intervening variables. For example, the Australian dollar was floated in late 1983 and there was some deregulation of stock exchanges, foreign bank ownership and mutual fund investment rules during 1984. The effects of these events (and others) on stock market volatility is uncertain and it is not a simple matter to disentangle these intervening events and extract a 'normal' model of expected volatility. Whilst it is acknowledged that these are potential confounding variables, never the less, for the tests employed it is assumed that they will have no effect.7

7 It could be easily argued that the net effect of these (additional) confounding variables would be to increase the volatility of the AOI stock market after 1983.
7.4.2 Data

For the purpose of testing this hypothesis, the daily 'price' of the Australian equities cash market was represented as the close of trading value of the Australian Stock Exchanges All Ordinaries Index (AOI). The daily closing prices of the AOI were obtained from the Sydney Stock Exchange for the period 2 February 1981 through 30 June 1987 (hereafter referred to as the AOI data set). The data set was restricted to about six years for two reasons. First, it was felt that the availability of two years of data prior to the introduction of the futures index was sufficient from which to obtain a measure of volatility prior to the first intervention. This is confirmed by other researchers including Working (1960), Powers (1970), Figlewski (1981) and Moriarity and Tosini (1985), who used similar testing periods. Secondly, the AOI series was not available prior to 1980 as Sydney and Melbourne stock exchanges published separate indices. While these indices can be combined into a single index using appropriate weighting factors, the choice of weighting factor is somewhat subjective.

To carry out an analysis of longer term variance effects the Wednesday closing price each week was chosen. This resulted in some loss of information in that day to day variations could not be examined. However as H(1) indicates, the major purpose of this chapter is to test for any increases in long term volatility which, if they exist, will be detected in weekly observations. The data set of weekly observations are equally spaced and appropriate time series analyses can be carried out on these data. A second approach was to analyse the daily data set as a measure of shorter term volatility [per Moriarity and Tosini (1985) and Hathaway (1986)]. The analyses of both series of weekly and of daily observations have been carried out with the results being reported later in this chapter.

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8 The volatility of the AOI back to January 1, 1980 was also tested but did not alter the conclusions.
7.4.3 Statistical Method

If \( P_t \) is the observed closing price at time \( t \) of the AOI, \( P_{t-1} \) is the price one period earlier (week or day, depending on the series being analysed) and \( \ln(P_t) \) is the natural logarithm of \( P_t \), following the methodology adopted in the previous chapter then:

\[
D_t = \ln \left( \frac{P_t}{P_{t-1}} \right) = \ln(P_t) - \ln(P_{t-1}).
\]

For \( t = 1, 2, \ldots \), if \( \{\ln(P_t)\} \) follows a random walk model then \( \{D_t, t = 1, 2, \ldots\} \) is a series of identically and independently distributed random variables.

As a measure of volatility \( (V^2) \), if \( N \) is the number of observations in the series, we take an estimate of the variance of \( \{D_t\} \) provided that this series is one of identically and independently distributed random variables i.e.

\[
V^2 = \left[ \frac{1}{N-1} \sum_{t=1}^{N} (D_t - \bar{D})^2 \right]
\]

where the sample mean

\[
\bar{D} = \frac{1}{N} \sum_{t=1}^{N} D_t.
\]

To determine the impact of the index futures and the index futures options index on the volatility of the AOI, what is required is a comparison of the volatility of the AOI before and after the introduction of trading in index futures, and similarly for index futures options.

To do this the population variance of the AOI is estimated for the AOI both before and after each intervention and then a test of equality of variances (which is equivalent to testing for a change in the level of volatility) is carried out, this test being based on the normal distribution [See Priestley (1981, pp.338-339)]. Indeed if \( V_B \) and \( V_A \)
represent the volatility in the series before and after the introduction of the intervention (the commencement of the futures index), testing $H(1)$ is equivalent to testing:

$$H_0 : \sigma^2_B = \sigma^2_A$$

where $\sigma^2_B$, $\sigma^2_A$ represent the population variances of the series before and after the intervention, and are estimated by $\hat{\sigma}^2_B$, $\hat{\sigma}^2_A$ respectively. If $\text{var}(\hat{\sigma}^2_B)$ represents the variance of $\hat{\sigma}^2_B$, with $\text{var}(\hat{\sigma}^2_A)$ similarly defined, when the hypothesis is true then:

$$\left( \frac{\hat{\sigma}^2_B - \hat{\sigma}^2_A}{\text{var}(\hat{\sigma}^2_B) + \text{var}(\hat{\sigma}^2_A)} \right)^{0.5}$$

is, asymptotically, normally distributed [see Appendix 7.1].

### 7.5 STATISTICAL RESULTS

#### 7.5.1 Effect of the SPI Futures - Weekly Data

To test the effect of the SPI on the volatility of the AOI, 101 weekly observations (closing price Wednesdays) of the AOI were taken prior to the introduction of SPI futures trading and 101 observations after this event and, in each case, 100 values of $D_t$ were determined. Appropriate time series models were fitted to each data set. Each model was in a form which enabled the data to be expressed as a general linear process [Equation (5.3.49) of Priestly (1981)], which is required for the application of the test of the hypothesis outlined in Appendix 7.1.

For both the pre and post intervention samples, the sample correlations were computed and used to compute estimates of the variance of both $\hat{\sigma}^2_B$ and $\hat{\sigma}^2_A$. For the pre-intervention series it was found that $\hat{\sigma}^2_B = 6.734 \times 10^{-4}$ and with sample standard deviation $1.217 \times 10^{-4}$ while for the post intervention series $\hat{\sigma}^2_A = 5.189 \times 10^{-4}$ with sample standard deviation $1.014 \times 10^{-4}$, the variance of the estimates, in each case, being computed from equation (A7.2). These values lead to a test statistic, computed
using (A7.1), of $Z = 0.975$. This test statistic is not significant at the 5% level of significance and so $H_0$, and hence $H(1)$, is accepted in the case of SPI futures.

This procedure was repeated taking 51 observations either side of the introduction of the futures index. The purpose of this was to see if there was a shorter term effect on the volatility of the AOI as a result of the introduction of the SPI. The repeated analysis resulted in a standardized normal Z value of 1.610 < 1.96, which indicates that the test statistic is again non-significant at the 5% level. Consequently the shorter data sets have also indicated no significant change in volatility.

7.5.2 Effect of SPI Futures Options - Weekly Data

A similar time series analysis was carried out on the AOI for two series of 101 weekly observations taken either side of the introduction of SPI futures options trading in June 1985. The application of the test in Appendix 7.1 led to a test statistic of 0.253 which is non-significant. This implies that trading in SPI futures options has not significantly changed the volatility of the AOI. An investigation of 50 weekly observations either side of the introduction of the futures options index led to the same conclusion.

7.5.3 Further Analyses

As indicated earlier a second approach is to analyse the daily data as an estimate of a shorter term volatility. A series of 257 daily closing values of the AOI was taken before and 253 values after the introduction of the SPI. Similarly, 254 daily AOI values were taken before the introduction of SPI index futures options trading and 253 values after this event. The test outlined in Appendix 7.1 was applied in each case and the results of both these analyses indicated that the volatility of the AOI was not affected by the individual interventions.

Finally, in order to determine if the combined effects of the SPI futures and the SPI futures options affected the volatility of the AOI, a comparison was made of the volatility of 101 weekly observations prior to the introduction of the SPI and of 101 weekly
observations after the introduction of futures options trading. The test based on the normal distribution indicated that at the 5% level of significance the combined effects of the introduction of trading in SPI futures and the SPI futures options did not have any significant effect on AOI volatility.

7.6 CONCLUSION

The introduction of the SPI futures trading in February 1983 and SPI futures options trading in June 1985, together with the availability of relevant data relating to the AOI, has enabled a number of statistical tests to be undertaken on the long run cash stock market volatility in Australia. Using time series techniques, the results indicate that the introduction of trading in the SPI futures and futures options markets has not affected the long term volatility of the AOI, either on a daily or weekly basis.

However, this conclusion must be qualified carefully. First, the tests employed have focused on a longer term volatility and did not consider the frequency or direction of price changes. Nor did they consider isolated price distortions in the cash market, such as short term expiration day effects. Moreover, no attempt was made to analyse whether futures lead or lag price changes in the cash market.

Further, there are a number of difficulties in designing tests to settle this research question. As with similar previous research the analysis in this chapter is a joint test of no change in volatility and no intervening effects. Any tests applied will involve a longitudinal study of the underlying stock index, by first identifying an event and then analysing the behaviour of the cash stock index before and after that event. But stock markets are affected by a large number of events over a period of time, so there is a problem of confounding or intervening variables. For example, the Australian dollar was floated in late 1983 and there was some deregulation of stock exchanges, foreign bank ownership and mutual fund investment rules during 1984. The effects of these events (and others) on stock market volatility is uncertain and it is not a simple matter to disentangle these intervening events and extract a 'normal' model of expected volatility.
Therefore, no cause-effect type analysis should be attempted due to the difficulties of deducing causation from correlation or statistical inference. Still, the analysis of Australian data in this chapter has reinforced the majority of the previous US studies that suggest that futures market trading has no effect on long run cash volatility.

This chapter has considered the possibility of volatility spillover from the futures market to the cash stock market and thus recognised the potential of feedback relationships between the two markets. The next two chapters analyse in a more formal sense the arbitrage relation between the SPI futures and AOI stock market. Chapter eight will formally outline the principle of intermarket arbitrage, document the intraday arbitrage series and test for the effects of overnight information on the mispricing series. The mean reversion in the arbitrage series will be tested in chapter nine.
Appendix 7.1

Estimation of the Variance Ratio

To test \( H_0 : \sigma_B^2 = \sigma_A^2 \), the distribution of \((\sigma_B^2 - \sigma_A^2)\) under \( H_0 \) is required. If \( \hat{\rho}_B(m), m=0, 1, 2, \ldots \) represents an estimate of the autocorrelation \( \rho_B(m) \) of the series \( \{D_t, t=1,w,\ldots\} \) before the intervention of interest (e.g. date of introduction of SPI futures trading), then following Priestly (1981), \( N^{1/2}(\sigma_B^2 - \sigma_A^2) \) is asymptotically normally distributed with mean zero and variance

\[
2\sigma_B^4 \sum_{m=-\infty}^{\infty} \hat{\rho}_B(m)
\]

[see Priestly p.339 and equation (5.3.28)]. In practice this variance is estimated as

\[
2\sigma_B^4 \sum_{m=0}^{p} \hat{\rho}_B^2(m) = 2\sigma_B^4 \left( 1 + 2 \sum_{m=1}^{p} \hat{\rho}_B^2(m) \right)
\]

with \( p = N/4 \).

These results are asymptotic but the data sets being considered here (minimum size 50) are sufficiently large for the asymptotic results to hold. In computing the estimate of the variance of \( \sigma_B^2 \) the maximum lag of the sample autocorrelation considered, is chosen as \( N/4 \). Based on these results, to test \( H_0 \), the test statistic

\[
Z = (\sigma_B^2 - \sigma_A^2) / \left[ \text{var}(\sigma_B^2) + \text{var}(\sigma_A^2) \right]^{0.5} \tag{A7.1}
\]

where

\[
\text{var}(\sigma_B^2) = 2\sigma_B^4 N^{-1} \left( 1 + 2 \sum_{m=1}^{p} \hat{\rho}_B^2(m) \right) \tag{A7.2}
\]

with \( \text{var}(\sigma_A^2) \) similarly defined, is, asymptotically, distributed as a standardised normal variable. Consequently, the computed value of \( Z \) can be compared with the appropriate critical value of the standardised normal distribution.
8.1 INTRODUCTION

Chapters four and six indicated that there were differential impacts from overnight information on opening stock and futures prices, distinct intraday patterns within stock and future markets, and that futures markets were consistently more volatile. This chapter continues the analysis of intermarket relationships, commenced in chapter seven, by documenting and analysing the arbitrage pricing between these two markets. It is well known that the availability of an underlying basket of stocks and a futures contract written on those stocks, provides an arbitrage link between cash and futures markets. The effectiveness of the link is dictated by a number of factors including the efficiency of markets, the expectations of participants in the market, transaction costs and the availability of arbitrage capital.

Considerable research has focussed on stock index arbitrage strategies and the documentation of deviations from 'fair values'. In an efficient market there should be no evidence of sustained arbitrage mispricing or any structural dependence in the mispricing series - the path of the series should fluctuate randomly around zero. The empirical observations have contrasted sharply with theoretical expectations. Researchers who used interday closing price data reported substantial and sustained mispricing between the cash index and futures markets. For example, see Cornell and French (1983), Figlewski (1984) Arditti, Ayadin, Mattu and Rigskee (1986) in the US, Bowers and Twite (1985) in Australia, Brenner, Subrahmanyam and Uno (1989) in Japan, and Yadav and Pope
One explanation put forward for these 'mispricings' was the immaturity of the arbitrage sector connecting the cash and futures markets. It was argued that a growing market takes some time to develop its arbitrage base sufficiently to eliminate arbitrage profits.¹ One other possible reason for the observed mispricings is that stock and futures markets do not have contemporaneous closing times.

More recent research has used intraday transaction data to obtain a contemporaneous arbitrage price and to undertake a micro level analysis of the evolution of the mispricing series. This research has found that: intraday arbitrage mispricing still remains (even after allowing for execution lags), there is strong and persistent positive autocorrelation in mispricing, and negative autocorrelation in the first difference of the mispricing series [MacKinlay and Ramaswamy (1988), Brennan and Schwartz (1990)], and there is some evidence that the degree of mispricing may vary between different markets or structures [Chung (1991), Lim (1992), Ho, Fang and Woo (1992)]. Such findings of sustained wave like mispricing indicates the availability of arbitrage profits which is not consistent with the hypothesis of market efficiency.

The above research, however, has largely ignored the impact of specific information flows or the widely differing microstructures of the stock and futures markets on the mispricing series. Such dependencies in the index futures mispricing series may be influenced by the microstructure of the futures market and the stock market. As has already been documented, the stock and futures markets differ in their methods of trading (open outcry compared with computer trading), the opening price setting mechanism, trading times, and the possibility that each market may be reacting to different information sets. In Australia, the actions of arbitrageurs serve to link together two very structurally different markets.

¹ Other researchers contend that arbitrage maturity will possibly not occur. For example, Rubinstein (1987, p.84) stated that after a five year period of market development: 'I am forced to the conclusion that even today the growth in index futures trading continues to outstrip the amounts of capital that are available for arbitrage.'
The above research is also limited in that it has concentrated on the large thickly traded markets of the US, with some recent extensions to the UK, Japan and Hong Kong. In order to externally validate the research in this area, an extension to a smaller market with a different economic and institutional environment, such as Australia, is desirable. Finally, in Australia, the published research has used closing price data and this introduces the possibility of measurement error because both markets do not close at the same time.

This chapter seeks to bridge some of the gaps in the empirical literature. The first contribution made is to document the intraday mispricing series using high frequency intraday data from the Australian market. A second contribution is to analyse the impact of overnight information on the opening arbitrage price and the effect over subsequent intraday arbitrage pricing. This is achieved by extending the transfer function modelling procedure developed in chapter four. Such an analysis is designed to ascertain whether there are statistically significant patterns in intraday mispricing, and to determine if observed patterns are related to structural or informational features or, indeed, if the actions of arbitrageurs overcome the nuances of individual markets.

The chapter is structured as follows. The arbitrage principle is formally outlined in section 8.2 and extended to index futures contracts in section 8.3. The calculation of the mispricing series is explained and justified in section 8.4. The empirical results are reported in section 8.5 and a summary and conclusions are contained in section 8.6.

8.2 THE ARBITRAGE PRINCIPLE

The importance of arbitrage conditions in financial economics has been recognised since Modigliani and Miller's (1958, 1963) classic work on the capital structure of the firm. They showed that if a firm could change its market value by simply adjusting its debt-to-equity ratio, then individual shareholders and bondholders could engage in portfolio
rebundling activities that would yield risk free profits. Modigliani and Miller's proof of this proposition applied an arbitrage argument.

Subsequently, financial economists have used arbitrage arguments to examine a variety of issues involving asset pricing. The assumption that arbitrage activity will quickly eliminate any 'free lunches' now serves as one of the more universally accepted postulates in the study of financial markets. Since this chapter applies the principle of arbitrage to determine a theoretical fair price for a stock index futures contract, it is instructive to closely examine and formally explain this principle.

Consider a market for assets with payoffs in different states of nature. These states need not be full-fledged Arrow-Debreu\(^2\) states of the world which describe all possible relevant circumstances; they are simply the outcomes of some random process. It is assumed that individuals care about their wealth in different states of nature, and prefer more wealth rather than less.

Let the payoff of asset \(a\) in state \(s\) be \(R_{sa}\), the number of assets be \(A\), and the number of states be \(S\). An asset is described by a vector giving its payoffs in each of the \(S\) states of nature. Thus, the first security is described by the column vector \((R_{11} \ldots R_{11})\) and the \(A\)th security is described by the column vector \((R_{1A} \ldots R_{SA})\). The payoff matrix of the entire set of assets is then represented by the matrix:

\[
R = \begin{bmatrix}
R_{11} & \ldots & R_{1A} \\
\vdots & \ddots & \vdots \\
R_{s1} & \ldots & R_{sA}
\end{bmatrix}
\]

\(^2\) An Arrow-Debreu primitive security is defined as a security that pays \(SR\) at the end of a period if a given state of nature occurs, and nothing if any other state occurs [Arrow (1964), Debreu (1959)].
The S by A matrix gives the payoffs of each of the A assets in each of the possible S states of nature. Each column of the payoff matrix represents a different security and each row gives the payoffs in a particular state of nature of each of the securities.

Let $x_a$ indicate the amount held of asset $a$. A portfolio of assets is then a column vector $x = (x_1, ..., x_A)$. The components of the portfolio $x$ can be of either sign. A positive value of $x_a$ indicates that one has a 'long' position in security $a$, and is entitled to receive the appropriate payoff if state $s$ materialises, and a negative value of $x_a$ indicates a 'short' position in the security so that one must pay out the appropriate amount if state $s$ occurs.

The wealth in state $s$ that one receives from holding a portfolio $x = (x_1, ..., x_A)$ is given by the expression:

$$w_s = \sum_{a=1}^{A} x_a R_{sa}$$

and in matrix notation:

$$
\begin{bmatrix}
W_1 \\
\vdots \\
W_S \\
\end{bmatrix} =
\begin{bmatrix}
R_{11} & \cdots & R_{1A} \\
\vdots & \ddots & \vdots \\
R_{S1} & \cdots & R_{SA} \\
\end{bmatrix}
\begin{bmatrix}
X_1 \\
\vdots \\
X_A \\
\end{bmatrix}
$$

Equation (8.1) illustrates the relationship between ends and means. The ends are the levels of wealth that the investor can achieve in the different states of nature and the means are the existing assets. By combining the existing assets into portfolios the investor can achieve different patterns of wealth across the states of nature, and the realised patterns of wealth will depend on the availability of tradeable assets. Thus, the market value of any single asset will depend on the availability of other assets to combine within a portfolio.
The optimal case will be determined when the full set of assets matches the number of states of nature and, therefore, any pattern of wealth can be achieved by some portfolio of existing assets. For example, in order to achieve a particular distribution of wealth, \( w = (w_1, \ldots, w_n) \), one solves the system of equations (as in the above matrix and assuming full rank) for the portfolio \( x = (x_1, \ldots, x_A) \) that attains that particular distribution of wealth. Since the system of equations will have as many unknowns as equations, it will always be possible to solve for such a portfolio.

If the assets outnumber the states of nature, there will be more unknowns than equations and several portfolios will exist that generate any particular distribution of wealth. Conversely, if the states of nature outnumber the available assets, then it will not be possible to solve the system of equations for all distributions of wealth. Some patterns of wealth cannot be constructed using the existing set of assets. This latter case is intuitively a more realistic description of economic reality.

When investors choose portfolios they are choosing a distribution of wealth across states of nature. In making this choice they are constrained by the amount of wealth they have available to invest and the prices of the various assets that they face. To express the idea of a budget constraint, let the price of asset \( A \) be denoted by \( P_A \) and let \( p = (P_1, \ldots, P_A) \) be the row vector of asset prices. The value of a portfolio \( x = (x_1, \ldots, x_A) \) will then be given by:

\[
px' = \sum_{a=1}^{A} P_a x_a
\]  

(8.2)

This formulation is similar to standard consumer theory where the value of a bundle of goods is expressed as the sum of expenditures on the various goods. The difference is that the goods that are being chosen (the assets) are not the ultimate end of consumption - they are only the means to an end. In the final analysis consumers are only concerned with the final distribution of wealth provided by different portfolios and therefore any two portfolios that provide the same pattern of wealth must be valued exactly the same.
Complete Security Markets

In a complete Arrow-Debreu economy, uncertainty about securities future values is represented by a full set of possible state-contingent payoffs. Linear combinations of this set of state-contingent security payoffs represent an individual's opportunity set of state-contingent portfolio payoffs. When the number of unique linearly independent securities is equal to the total number of alternative future states, the market is said to be complete and all possible security payoffs can be constructed from a portfolio of the existing securities. If the market is incomplete then not every security payoff can be constructed from a portfolio of the existing securities.

Given, however, a complete securities market the uncertainty about the value of future wealth could be reduced to zero, regardless of which state of nature actually occurred. By dividing wealth in an appropriate way amongst the available securities, a portfolio could be constructed that was equivalent to holding equal amounts of all the primitive securities. This portfolio would have the same payoff in every state of nature even though the payoffs of individual securities varied over states. Since the payoff pattern of any security can be achieved by some portfolio of Arrow-Debreu securities, the price of the security must be equal to the price of the portfolio of Arrow-Debreu securities that realises that same distribution of wealth across the states of nature. This brings up the notion of arbitrage.

No Arbitrage Profit Condition

If short selling is allowed, then a second related condition for market equilibrium is the absence of riskless arbitrage profit opportunities. In the context of the complete market state-preference framework market equilibrium dictates that any two securities, or portfolios with the same state-contingent payoff vectors, must be priced identically.

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3 See Ross (1976a). Ross (1976b) also showed that if derivative options can be written on market securities with viable payoffs across states of nature, then an infinite number of linearly independent security and option payoffs can be formed from a small number of securities.
Otherwise, traders would purchase the security or portfolio with the lower price and sell the security or portfolio with the higher price. For example, when two portfolios, A and B, sell at different prices ($\rho_A > \rho_B$), but have identical state contingent payoff vectors, then an arbitrageur could short sell the more expensive portfolio and realise a cash flow of $\rho_A$. The arbitrageur could then use the proceeds to purchase the lower cost portfolio ($\rho_B$) to realise a positive arbitrage cash flow of ($\rho_A - \rho_B$), and repay the short position in $\rho_A$.

In short, in a perfect and complete security market setting any market security's payoff vector can be replicated by a portfolio of pure securities. The no arbitrage condition requires that the price of that market security be equal to the price of any linear combination of primitive securities that replicates the security's payoff vector.

### 8.3 Arbitrage and Index Futures

The above approach can be applied to futures markets since a futures market extends the available intertemporal payoffs, the introduction of futures trading can be viewed as shifting an economy towards a more complete Arrow-Debreu economy [see Ross (1976) and footnote 3]. The availability of futures markets means that traders can observe and lock in current and ex-ante prices for the traded futures commodity. The futures commodity can then be valued in terms of the current spot price, the ex-ante price and holding costs. This means that the theoretical 'fair value' price of a futures contract can be determined by an arbitrage relationship between the physical asset and its related futures contract.

The arguments underlying the valuation of an index futures contract exploit the availability of a replicating portfolio of underlying shares whose cumulative value coincides with the price of the futures index at its expiration date. In frictionless markets, the availability of a perfect substitute for the futures index guarantees that if the opportunity for a profit arises, then these would attract the action of 'arbitrageurs' who would quickly close the gap between the price of the index futures contract and the underlying basket of shares.
Assume that markets are perfect and frictionless, that borrowing and lending can take place at a constant continuously compounded interest rate \( r \), that deposit and performance margins can be posted in interest bearing assets, and that a basket of shares pays dividends continuously at a rate \( d \). Consider the following share portfolio, constructed at current time \( t \), and held until the futures contract expires at date \( T \):

(i) Buy the basket of shares at the existing market price \( I_t \) (the AOI index) and continuously reinvest the dividends received until expiry at \( T \);
(ii) Borrow \( SI_t \) at time \( t \) to finance the acquisition;
(iii) Sell a futures contract at the currently quoted futures price \( F_{t,T} \).

Given perfect and complete markets this portfolio is costless\(^4\) at \( t \), and it can be shown that the theoretical fair price of a futures contract with maturity date \( T \) is [Cornell and French (1983) MacKinlay and Ramaswamy, (1988)]:

\[
F_{t,T} = I_t e^{(r-d)(T-t)}
\]  

(8.3)

The right hand side of equation (8.3) expresses the theoretical (fair) futures price as the cost of carrying the index basket of stocks to maturity. Where:

- \( F_{t,T} \) is the theoretical futures price at time \( t \) for a futures contract expiring at \( T \),
- \( I_t \) is the AOI index price at \( t \),
- \( e \) is the exponential function,
- \( r(T-t) \) is the yield at time \( t \) of a discount bond maturing at time \( T \), and
- \( d(T-t) \) is the continuous dividend yield over time \( t \) to \( T \).

Interest and dividend rates are assumed to be constant for the duration of the futures contract.

In an efficient market without transaction costs there should be no deviation of the traded index futures price from its theoretical value. Any mispricing would result in a profitable, risk free, arbitrage opportunity. For example, if the traded futures price \( F_{tm,T} \) at time \( t \)

\(^4\) The portfolio is only 'costless' when there are no transaction costs, zero risk and complete certainty. These assumptions are discussed at length later in the chapter.
is greater than $I_t e^{(r-d)(T-t)}$, then the appropriate arbitrage action would be to sell the index futures contract and buy the underlying basket of stocks. The stock purchase is financed by borrowing at the risk free rate and the riskless arbitrage profit amounts to $F_{lm,T} - I_t e^{(r-d)(T-t)}$. If $F_{lm,T}$ is less than $I_t e^{(r-d)(T-t)}$, then the arbitrageur would sell the index and invest the proceeds at the risk free rate to give a profit of $I_t e^{(r-d)(T-t)} - F_{lm,T}$.

### 8.4 Calculation of the Mispricing Series

In this chapter arbitrage mispricing $M_{t,T}$ of a futures contract maturing at $T$ is defined according to Yadav and Pope (1992) as:

$$M_{t,T} = \left[ \ln(F_{tm,T}) - \ln(F_{t,T}) \right]$$

(8.4)

where

- $\ln$ is the natural logarithm,
- $F_{tm,T}$ is the spot market price time $t$ for a forward contract expiring at $T$, and
- $F_{t,T}$ is the theoretical futures price at time $t$ for a forward contract expiring at $T$.

The theoretical futures price given by equation (8.3) makes several simplifying assumptions, which if taken into account, would reduce the bounds of profitable arbitrage. These assumptions are: there are no transaction costs; dividends are known ex ante with certainty; interest rates are non stochastic; futures are not marked to market on a daily basis; markets are continuous and complete; and forward and futures prices are equivalent. The impact of these assumptions is discussed below.

#### 8.4.1 Transaction Costs

The introduction of transaction costs to the formula reduces the size of arbitrage profits. A common practice has been to define the transaction costs bounds as:

---

5 The use of the log relativity has been preferred to a simple price difference model because it reduces potential heteroscedasticity problems.
\[ M_{t,T} = (T_s + I_s + T_f + I_f) \]

where

- \( T_s \) is the percentage round trip stock commission,
- \( T_f \) is the percentage round trip futures commission,
- \( I_s \) is the percentage trading price impact in stocks, and
- \( I_f \) is the percentage trading price impact in futures.

The existence of transaction costs implies that mispricing within transaction cost bounds would be consistent with market efficiency. However, even after adjustment for transaction costs, index futures mispricing has been regularly observed in the S&P 500 contract in the US [Figlewski (1984), Merrick (1988), Finnerty and Park (1988), and MacKinlay and Ramaswamy (1988]), and also in the UK [Yadav and Pope (1990)].

A number of researchers point out that the transaction cost argument may well be overstated and that there are a number of factors which reduce the transaction cost band. Figlewski (1984) and Rubinstein (1987) note that well diversified institutions need not resort to short sales to take advantage of profitable arbitrage opportunities and that their transaction costs are relatively small. MacKinlay and Ramaswamy (1988) note that rollover strategies (carrying forward the arbitrage to the next maturity month), only require market impact and transaction costs in the futures market, as the replicating portfolio is already set up in the stock market. Yadav and Pope (1990) argued that there is a hierarchy of transaction costs and that the appropriate transaction costs are those of the lowest cost marginal trader, which is considerably lower than is commonly estimated.

On the other hand, the transaction cost band will increase with greater rebalancing of the replicating portfolio. This is more likely to occur with replicating portfolios which employ less than the full basket of stocks and therefore must allow for a greater tracking margin of error. This will increase with longer time to expiration but will be offset by lower initial setup costs.
The calculation of the mispricing series in this chapter did not incorporate transaction costs for a number of reasons. First, there is likely to be a hierarchy of transaction costs. The costs incurred by brokers and market makers are substantially less than for institutions which in turn have lower costs than small investors. Secondly, whilst futures related transactions costs are lower than those in the stock market, if a diversified portfolio of stocks is already held, then there are no costs involved in setting up a replicating portfolio. Costs are unlikely to be fixed in such a varied and dynamic environment. It is therefore unlikely that the selected transaction cost would represent the boundary of efficient arbitrage.

8.4.2 Nonstochastic Interest Rates and Dividends

Stochastic interest rates and dividends will reduce the arbitrage bounds. Unanticipated changes in interest rates will increase the cost of financing the marked-to-market margins on the futures contract. Unanticipated changes in dividends will increase dividend risk. Cox, Ingersoll and Ross (1981) and Whaley (1986) have further shown that the assumption that forward and futures contracts are equivalent only holds when interest rates are nonstochastic.

In practical terms, however, the analyses by Rendleman and Carabini (1979), Cornell and Reinganum (1981), and Elton, Gruber and Rentzler (1984) indicate that the differences between futures and forward prices are insignificant (including the marked to market feature of futures contracts), and can be safely ignored. The stochastic effect of interest rates on mispricing has been considered by Modest (1984) who concluded that the impact was minimal. Regardless of this, the effects of interest rate risk can easily be mitigated by hedging interest rate risk in the futures market.

In the calculation of the mispricing series the fixed term 90 day bank bill rate was used as a proxy for the risk free rate because it approximates the holding period for the futures contract. These rates were obtained on a daily basis from the Australian Financial Review. Dividend yields were obtained from the Australian Stock Exchange publication
'Monthly Index Analysis'. It was assumed that the dividend yield for the previous month was the best estimate of the dividend yield for the remainder of the futures contract. This dividend expectations model was used for two reasons. First, it contributes to the ex ante nature of the tests, and secondly the dividend yields were relatively constant over the sample period.

8.4.3 Incomplete Markets

The existence of stale prices or nonsynchronous trading can cause autocorrelations in the cash index price and may lead to arbitrage opportunities being falsely identified. Empirical investigations by Harris (1989), MacKinlay and Ramaswamy (1988), and Miller, Muthuswamy and Whaley (1994) concluded that cash index returns are autocorrelated even after the effects of nonsynchronous trading are removed. Further, the analysis in chapter six showed that autocorrelation in the Australian Twenty Leaders Index is still evident even though trading is very liquid in those shares. No adjustment was made for this effect, but some of the tests carried out later in the chapter control for this effect.

8.4.4 Factors Which Reduce Arbitrage Risk

A factor that may offset some of the risks and the costs associated with arbitrage is that arbitrageurs have the option either to close the position prematurely, or to roll forward the position to the next contract [Brennan and Schwartz (1987)]. These trading choices represent an option that arbitrageurs may choose to invoke. If profits increase above those contracted by the original arbitrage then these profits may be realised by novating the original position. However, if profits from the original arbitrage are progressively reduced then the optimal strategy for the arbitrageur is to simply hold the original hedge position and take the riskless profit. Consequently, profits are bounded below but are potentially unbounded on the upside and this feature somewhat reduces the risk of arbitrage. In accordance with option pricing theory the value of this option feature would be directly related to the volatility of the mispricing series - the higher the volatility the
greater the value [Brace and Hodgson (1991)]. This result seems counter-intuitive, but it is not altogether inconceivable that the risk faced by arbitrageurs in a small volatile market, like Australia, may in fact be lower than in larger more liquid and less volatile markets.

One important component related to the value of this option is the stochastic behaviour of the mispricing series. If the cost of carry deviations are relatively predictable (i.e. if mispricings are correlated), then an arbitrageur will be more certain of the optimal time to close the position. This feature will reduce the uncertainty regarding the direction of the movement in mispricing and effectively reduce the value of the option. The ability to predict the direction of the mispricing series enhances the probability of a positive arbitrage profit.

The results of these problems have significant implications for all market participants. Predictable prices enable hedgers, speculators, financial managers and analysts to design optimal policies that exploit any price patterns. An affirmative answer to any of the above questions implies the existence of arbitrage profit which is inconsistent with market efficiency. Therefore, the above research questions are aimed to test the intraday efficiency of the Australian cash and futures markets. The empirical results may also contribute to a further understanding of market microstructure. All of the research questions are proposed in order to compensate for the lack of a positive, descriptive theory of intraday arbitrage price behaviour in the Australian stock and index futures markets.

8.5 DATA AND RESULTS

8.5.1 Data

The data set used in this chapter is the high frequency intraday data described in chapter four. It consists of 15 minute observations of cash and futures data for the AOI stock
market index and the SPI futures contract from 1 April 1992 to 30 March 1993. The data relates only to the near futures contract, shifting to the next contract at the expiration date of the near contract. Stock and futures markets do not always trade at the same time and in order to calculate theoretical futures prices and the subsequent mispricing series, contemporaneous cash and futures prices are required. This meant that the 0950 and 1610 SPI futures prices and the lunchtime AOI cash prices after 1230 and before 1400 were dropped. The morning of 24 August 1992 was also dropped because there was no trading on the stock exchanges. This left a total of 5009 matched observations to calculate theoretical prices.

8.5.2 Results

Descriptive Statistics

Table 8.1 panel A, summarises the descriptive statistics for the SPI futures contract mispricing series. The average mispricing is positive (0.00038) with an overall standard deviation of 0.00522. There is no significant skewness or kurtosis, and stem and leaf and normal probability plots show that the series is otherwise statistically well behaved and normally distributed. Slightly more than half of the observations (53.9%) are positively mispriced. If a transaction cost boundary of 0.5% is assumed [MacKinlay and Ramaswamy (1988)], then 37% of the observations violate this ex post test, with 20.5% being positive violations and 16.5% negative violations.

The autocorrelation coefficients for the first eight lags are reported in Table 8.1 panel B and they indicate that the mispricing levels are highly autocorrelated. The first order autocorrelation coefficient is positive and high (0.649), and positive and significant for six of the eight lags reported. When the series is broken down into the four component futures contracts, first order autocorrelation is found to be consistently high across contracts (in the range 0.581 to 0.696). A tendency for a given futures contract to have mostly upper-bound violations or mostly lower-bound violations (but not both) is further

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6 MacKinlay and Ramaswamy (1988) observed the following results for the mispricing series (μ = 0.12% and σ = 0.44%) measured as a percentage of the stock index value.
evidence that the mispricing series is path dependent. An examination of the descriptive
statistics in Table 8.1, panel A shows that each contract is dominated by either positive or
negative mispricings. For example, in the June 1992 contract 75.1% of the mispricings
are positive with 30.1% violating a hypothetical upper bound transaction cost boundary of
0.5%. In contrast, only 5.1% violate the 0.5% lower bound transaction boundary. The
path dependent nature of the mispricing series can also be observed in Figure 8.1, panels
A-D which plots the theoretical mispricing series over the four futures contract periods.
Overall these results indicate that mispricing tends to remain above or below zero, does
not fluctuate randomly around zero, and the results are robust across different futures
contracts.

| Table 8.1 |
| Summary Statistics for the Mispricing Series |

| Panel A |
| Series | Number | Mean | Stdev | Skewness | Kurtosis | Positive(%) | > +0.5% | < -0.5% | Warsaw: 1980 |
| Full | 5009 | 0.00038 | 0.00522 | -0.096 | -0.383 | 53.9 | 20.5 | 16.5 | 0.43 |
| Jun 92 | 1240 | 0.00262 | 0.00434 | -0.112 | -0.402 | 75.1 | 30.1 | 5.1 | 1.87 |
| Sep 92 | 1289 | -0.00220 | 0.00321 | 0.368 | 0.208 | 23.2 | 3.3 | 19.9 | -2.34 |
| Dec 92 | 1240 | -0.00552 | -0.054 | -0.744 | 36.8 | 11.4 | 34.1 | -1.51 |
| Mar 93 | 1240 | 0.00339 | 0.00475 | -0.619 | 0.521 | 81.5 | 38.8 | 6.6 | 2.49 |

* t statistic is adjusted for the time series dependency in the data

| Panel B |
| Autocorrelation Lag - |

| Series | Number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Full | 5009 | 0.649 | 0.158 | 0.067 | 0.059 | -0.023 | 0.035 | -0.008 | 0.037 |
| Jun 92 | 1240 | 0.594 | 0.189 | 0.084 | 0.074 | -0.028 | 0.015 | 0.041 | 0.010 |
| Sep 92 | 1289 | 0.696 | 0.065 | 0.062 | 0.066 | 0.027 | -0.032 | 0.055 | 0.030 |
| Dec 92 | 1240 | 0.696 | 0.136 | 0.067 | 0.034 | -0.028 | 0.056 | -0.047 | 0.064 |
| Mar 93 | 1240 | 0.581 | 0.208 | 0.074 | 0.062 | -0.030 | 0.072 | -0.030 | 0.043 |
Figure 8.1 Mispricing series for the AOI and SPI
Figure 8.1  Mispricing series for the AOI and SPI (continued)
Figure 8.2 Mean and standard deviation of intraday mispricing

Figure 8.3. Intraday mispricing - Friday compared to the rest of the week
**Intraday and Seasonal Mispricing**

The mispricing series is decomposed into intraday periods with the descriptive statistics shown in Table 8.2, and the mean and standard deviation plotted in Figure 8.2. The average intraday mispricing is positive and fairly constant up to the lunchtime close at 1230. After lunch average mispricing is lower than in the morning and the close of arbitrage trading (1600 hours) the mispricing becomes negative. The intraday standard deviation remains constant over the trading day.

**Table 8.2**

**Descriptive Statistics for the Intraday Mispricing Series**

<table>
<thead>
<tr>
<th>Time</th>
<th>Mean</th>
<th>Stdev</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>0.000468</td>
<td>0.00599</td>
<td>-0.201</td>
<td>-0.561</td>
</tr>
<tr>
<td>1015</td>
<td>0.000430</td>
<td>0.00536</td>
<td>-0.127</td>
<td>-0.612</td>
</tr>
<tr>
<td>1030</td>
<td>0.000389</td>
<td>0.00523</td>
<td>-0.164</td>
<td>-0.372</td>
</tr>
<tr>
<td>1045</td>
<td>0.000508</td>
<td>0.00522</td>
<td>-0.179</td>
<td>-0.389</td>
</tr>
<tr>
<td>1100</td>
<td>0.000467</td>
<td>0.00508</td>
<td>-0.213</td>
<td>-0.439</td>
</tr>
<tr>
<td>1115</td>
<td>0.000435</td>
<td>0.00495</td>
<td>-0.081</td>
<td>-0.423</td>
</tr>
<tr>
<td>1130</td>
<td>0.000425</td>
<td>0.00505</td>
<td>-0.164</td>
<td>-0.162</td>
</tr>
<tr>
<td>1145</td>
<td>0.000464</td>
<td>0.00505</td>
<td>-0.022</td>
<td>-0.429</td>
</tr>
<tr>
<td>1200</td>
<td>0.000414</td>
<td>0.00523</td>
<td>-0.032</td>
<td>-0.419</td>
</tr>
<tr>
<td>1215</td>
<td>0.000385</td>
<td>0.00520</td>
<td>0.029</td>
<td>-0.452</td>
</tr>
<tr>
<td>1230</td>
<td>0.000507</td>
<td>0.00530</td>
<td>-0.028</td>
<td>-0.518</td>
</tr>
<tr>
<td>1400</td>
<td>0.000421</td>
<td>0.00528</td>
<td>-0.045</td>
<td>-0.391</td>
</tr>
<tr>
<td>1415</td>
<td>0.000302</td>
<td>0.00527</td>
<td>-0.097</td>
<td>-0.353</td>
</tr>
<tr>
<td>1430</td>
<td>0.000270</td>
<td>0.00531</td>
<td>-0.083</td>
<td>-0.116</td>
</tr>
<tr>
<td>1445</td>
<td>0.000373</td>
<td>0.00516</td>
<td>-0.080</td>
<td>-0.239</td>
</tr>
<tr>
<td>1500</td>
<td>0.000376</td>
<td>0.00503</td>
<td>-0.128</td>
<td>-0.135</td>
</tr>
<tr>
<td>1515</td>
<td>0.000353</td>
<td>0.00514</td>
<td>-0.163</td>
<td>-0.454</td>
</tr>
<tr>
<td>1530</td>
<td>0.000333</td>
<td>0.00511</td>
<td>-0.109</td>
<td>-0.443</td>
</tr>
<tr>
<td>1545</td>
<td>0.000338</td>
<td>0.00529</td>
<td>-0.109</td>
<td>-0.429</td>
</tr>
<tr>
<td>1600</td>
<td>-0.000061</td>
<td>0.00522</td>
<td>0.099</td>
<td>-0.115</td>
</tr>
</tbody>
</table>

The possibility that mispricing may vary across days of the week and time of the day is examined by decomposing the mispricing data into days of the week. Mispricing did not significantly vary across days of the week from Monday through Thursday for specific intraday periods. However, when the intraday mispricing pattern for Friday was compared to the average intraday pattern for the rest of the week it showed that the mispricing level began to fall before lunchtime on Friday and stayed at around or below
zero until a large negative drop at close. The comparison of Friday's intraday mispricing compared to the rest of the week is plotted in Figure 8.3. For the remainder of the week the mispricing series is positive and relatively constant until the close of arbitrage trading at 1600. This pattern is similar to the negative Friday afternoon patterns observed in stock and futures returns in the US [Ekman (1992), and Finnerty and Park (1988)].

These results suggest two conclusions: (i) a consistent and strong decline in mispricing at or around the close of arbitrage trading on all days of the week; and (ii) a decline on Fridays which commences in the late morning and continues through the afternoon.

The Impact of Overnight Information

This section extends the previous sections by analysing the impact of overnight information on the mispricing series. The statistical method adopted is the time series transfer function modelling which takes account of interventions (see chapter four). The relevant overnight information is assumed to be the previous day's log relative change in the DJ65 and $M_t$ is the current level of mispricing:

$$M_t = \alpha + \sum_{i=1}^{q} \Psi_i M_{t-i} + \sum_{j=1}^{n} \delta_j X_{j} + \nu(B) I_t + \varepsilon_t$$

(8.6)

where

- $\sum_{i=1}^{q} \Psi_i M_{t-i}$ represents the autoregressive time series effects from previous mispricing;
- $\sum_{j=1}^{n} \delta_j X_{j}$ represents significant spikes in intraday mispricing;
- $\nu(B) I_t$ represents the impact of an input variable ($I_t$) on $M_t$. The intervention ($I_t$) is the impact of the previous day's return from the DJ65 Stock Composite Index on the opening 1000 mispricing; and $\nu(B)$ is the transfer function to be estimated; and

---

7 Following previous research, a standard unadjusted F-test suggested that there was no difference in intraday mispricing from Monday to Thursday (F-test=1.45), but Friday's intraday mispricing showed significant difference from the remainder of the week at the 10% level (F-test=3.59).
\( \epsilon_t \) is the residual term.

Applying the same techniques outlined in chapter four the intervention, transfer and noise components of the model were estimated simultaneously by maximum likelihood estimation. The results are reported in Table 8.3. They confirm the US results of a strong and persistent autocorrelation in mispricing up to four lags (1 hour), with the coefficients at lag 8 (2 hours) and lag 40 (2 days) also positive and significant. The mispricing spike at close was negative and significantly different from other mispricings through the day. The intervention and transfer function for the overnight impact from the previous day's return on the DJ65 on the opening and subsequent mispricings has the following form:

\[
\left[ \frac{\gamma_0}{1 - \beta_1 B} \right] \text{DJ65}
\]  

(8.7)

where

- DJ65 is the previous day's log relative return on the DJ65 Composite Index,
- \( \gamma_0 \) is the coefficient of impact of the DJ65 return on the opening mispricing, and
- \( (1 - \beta_1 B)^{-1} \) is the transfer function which is defined as a polynomial in lag B.

The coefficient of the US impact at opening is positive and highly significant (coefficient \( \gamma_0 \) in Table 8.3). This means that positive returns in the US will invoke an increase in the Australian mispricing spread and negative overnight returns in the US will result in a decrease in the mispricing spread. For example, if the overnight return in the US is 0.05 then this will further increase the mispricing at opening (which is on average 0.00047) by some 18.6\%. The transfer function impulse response weight (coefficient \( \beta_1 \) in Table 8.3) has a third lag coefficient significant to three lags and this means that on average the total impact will last for one hour. These results, along with the autoregressive coefficients, suggest that the mispricing series in Australia has a memory lag of approximately one hour.

\[ \text{Calculated as } \left[\frac{0.05 \ast 0.00174}{0.000468}\right]. \]
Table 8.3

Results: Maximum Likelihood Estimation of the Intraday Mispricing Series

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>T Ratio</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\alpha$</td>
<td>0.00037</td>
<td>0.32</td>
</tr>
<tr>
<td>2</td>
<td>$\Psi_1$</td>
<td>0.66397</td>
<td>46.94</td>
</tr>
<tr>
<td>3</td>
<td>$\Psi_2$</td>
<td>0.15187</td>
<td>8.94</td>
</tr>
<tr>
<td>4</td>
<td>$\Psi_3$</td>
<td>0.05113</td>
<td>3.00</td>
</tr>
<tr>
<td>5</td>
<td>$\Psi_4$</td>
<td>0.06212</td>
<td>4.10</td>
</tr>
<tr>
<td>6</td>
<td>$\Psi_5$</td>
<td>0.02790</td>
<td>2.80</td>
</tr>
<tr>
<td>7</td>
<td>$\Psi_6$</td>
<td>0.02555</td>
<td>4.49</td>
</tr>
<tr>
<td>8</td>
<td>$\gamma_0$</td>
<td>0.00174</td>
<td>15.06</td>
</tr>
<tr>
<td>9</td>
<td>$\beta_1$</td>
<td>0.14886</td>
<td>2.32</td>
</tr>
<tr>
<td>10</td>
<td>$\delta_1$</td>
<td>-0.00043</td>
<td>-5.61</td>
</tr>
</tbody>
</table>

Residual Analysis

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>Variance</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0000077</td>
<td></td>
<td>0.0000021</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.0095</td>
<td>Num &gt; 0</td>
<td>2520</td>
</tr>
<tr>
<td>$t$ for mean = 0</td>
<td>0.37</td>
<td>Schwartz BC</td>
<td>-50870.11</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1.32</td>
<td>Number of residuals</td>
<td>4985</td>
</tr>
<tr>
<td>Chi-square lag 24</td>
<td>14.28</td>
<td>Chi-square lag 42</td>
<td>31.06</td>
</tr>
</tbody>
</table>

It may be argued that these results are driven by thin trading in the underlying stock index. This thin trading hypothesis means that in a bull market the futures price will reflect information more quickly than the stock index. This in turn would lead to a positive increase in the average mispricing spread and vice versa for a bear market. Empirically, the mispricing series should deviate at or around an information release and revert back towards zero as trading in the underlying stocks reveals price information which is then incorporated in the AOI. This proposition was tested by visually examining the mispricing series on bull and bear trading days. If nonsynchronous trading was a factor in driving the mispricing series then mispricings should initially be positive and decline towards the end of a bull day, and the opposite should happen for bear days. In general, the opposite was true. On bull days the mispricing levels consistently plotted below the mispricing levels observed on bear days and this gap was wider in the mornings compared to the afternoons.

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9 A bull trading day was defined when the cumulative returns from 1015 to 1600 were positive, and conversely for a bear day.
8.6 SUMMARY AND CONCLUSIONS

This chapter outlined the arbitrage principle and applied that principle to establish a fair value for a stock price index futures contract. The mispricing series for the stock price index contract is then calculated using the actual traded price and the theoretical futures price. Consistent with previous overseas studies, the mispricing series did not fluctuate randomly around zero. The series had a high positive autocorrelation coefficient at the first lag and was positive and significant up to at least four lags with the series consistently remaining above and below zero for prolonged periods. These results were robust across the four contracts examined.

Intraday mispricing was examined and the mispricing did not show any significant difference across days of the week except for a tendency for the positive mispricing to decay from the late morning period on Fridays. Mispricing at close of arbitrage trading showed a sharp decline and was significantly different from mispricing at other times during the day.

Overnight information, modelled as the previous days return on the DJ65 Composite Index, had a positive impact on the mispricing series at the opening of trading of the Australian market. Previous day increases in the DJ65 increased the mispricing spread and decreases reduced the spread. This impact was transferred across into three subsequent 15-minute periods. The contention that this effect was driven by the thin trading problem in the stocks which constitute the AOI was examined by splitting the mispricing series into bull and bear days. It was found that intraday mispricing was positive and declined over the course of bear days and that the mispricing series increased during trading on bull days which is opposite to the predictions of the nonsynchronous trading hypothesis.

Chapter nine extends the analysis undertaken in this chapter by examining the strength of arbitrage activity and the impact on the mispricing series across time periods and factors associated with economic and microstructures. This analysis is undertaken by testing for mean reversion in the arbitrage series.
9.1 INTRODUCTION

Empirical research relating to the mean reversion of asset prices and returns has assumed importance as a research paradigm over the last few years for a number of reasons. First, a mean reversion process implies that there are predictable patterns in security markets and challenges the assumption that markets are 'weak form efficient'. Second, in arbitrage markets such as futures and cash markets, an economically defensible fundamental value can be derived. In this context the formal measure of the strength of the mean reversion parameter can provide an insight into the importance of arbitrage activity in determining the efficiency of market prices. Further, by extending the analysis down to the microstructure of the market, evidence can be gathered on the seasonality of the arbitrage link between cash and futures markets and on how mean reversion varies across trading structures, information flows, and geographical boundaries.

In a mean reversion process, prices are expected to change back toward a fundamental value whenever market forces push the price sufficiently far from that value.\(^1\) Mean reversion has been attributed to a number of factors. For example, 'bandwagon' effect [Poterba and Summers (1988)]; the actions of 'noise' traders who follow price fads induced by self-fulfilling expectations [Samuelson (1967), Shiller (1986)]; or the over-reaction hypothesis whereby participants in a market overweight the value of new information and underweight the value of old information [De Bont and Thaler (1985, 1987)].

\(^1\) There are a number of hypotheses about the factors which cause prices to deviate from fundamental value and result in mean reversion. The 'bandwagon' effect [Poterba and Summers (1988)]; the actions of 'noise' traders who follow price fads induced by self-fulfilling expectations [Samuelson (1967), Shiller (1986)]; or the over-reaction hypothesis whereby participants in a market overweight the value of new information and underweight the value of old information [De Bont and Thaler (1985, 1987)], are some examples.
reversion will occur when more efficient traders realise that the fundamental value at current time \( t \) (\( FV_t \)) is greater or less than the current market price (\( P_t \)). If \( FV_t - P_t < 0 \), then the expected change in the stock price will be negative and vice-versa. If deviations from fundamentals are seen to be caused by 'noise' traders, then the extent of the mean reversion can also be seen as a measure of the speed of reaction of arbitrage price traders.

For example, if prices are 'strongly mean reverting', then once prices depart from the fundamental value they return to that level very quickly - this implies a high response supply elasticity of traders who trade on price deviations. On the other hand if prices are 'weakly mean reverting' this implies a low response elasticity or evidence that the activities of noise traders are still influential. In a well functioning and competitive price market one would expect any deviations from fundamental value to be eliminated fairly quickly.

Chapter eight established the existence of persistent mispricing between the actual traded futures price and the theoretical futures price but there was no analysis of the behaviour of the first difference of that series. MacKinlay and Ramaswamy (1988), Lim (1990), Yadav and Pope (1990) and Miller, Muthuswamy and Whaley (1994) find negative autocorrelation in changes of the cash-futures basis. Yadav and Pope (1993a) formally analyse mean reversion of the mispricing series in the US and the UK markets and find distinct patterns in the mean reversion parameters. The first contribution of this chapter is to extend the above empirical evidence on the mean reversion parameter in the mispricing series to the Australian market. Mean reversion is defined as the existence of a negative relationship between changes in mispricing and the level of mispricing in the previous period [Yadav and Pope (1993a)]. The extension of this research to Australia is important because of the different trading structures, especially the fact that there is a high amount of infrequent trading in the underlying stocks which constitute the AOI and the debate in the literature that mean reversion is a 'statistical illusion' caused by infrequent trading.
A second contribution of this chapter is to provide empirical evidence on how the mean reversion parameter may vary with microstructural or market induced factors. The rational information models of Kyle (1985) and Admati and Pfleiderer (1988) predict that rational arbitrage induced traders would be more active at the open and close of trading; whilst the noise trading models of Samuelson (1967), Shiller (1986), De Bont and Thaler (1985, 1987) and Poterba and Summers (1988) predict that the excess trading of speculators would overcome the actions of arbitrageurs in periods of high volume. Vaidyanathan and Krehbiel (1992) provided a further scenario by suggesting that arbitrage activity between markets with structural differences causes fluctuations in the mispricing series, and that increasing the strength of arbitrage, serves to increase the fluctuations. Yadav and Pope (1993a) analyse the behaviour of the mean reversion parameter as a function of the level of mispricing, time to maturity of the futures contract, day of the week and hour of the day. This microstructure research on mean reversion is replicated and extended in this chapter.

The remainder of this chapter is structured as follows. To give an overview and to establish the importance of the mean reversion research paradigm, section 9.2 first reviews the prior studies which analysed mean reversion in security prices. This section is then extended to review mean reversion in mispricing between the cash stock and futures index markets. Section 9.3 formally describes a general model in the form of an Ornstein-Uhlenbeck mean reverting process and then outlines the Dickey-Fuller statistical technique which is used to empirically test for mean reversion in the data. Section 9.4 reports the empirical results and section 9.5 concludes the chapter.

9.2 BACKGROUND

9.2.1 The Importance of the Mean-Reversion Research Paradigm

A number of research programs in financial economics make the assumption that rational economic agents employ the available information set to maximise expected utility in terms of market prices. This implies that all relevant information is impounded in security
prices and has led to the propositions that security markets do not have 'memories', ex ante price movements cannot be predicted from past prices, and there are no 'free lunches' in financial markets. Intuitively, if information (both good and bad) is supplied in a random fashion and is impounded in an unbiased manner, then prices should follow unpredictable time series patterns [Fama (1965)]. Most of the empirical research on market efficiency undertaken during the 1970's and 1980's appears to demonstrate an efficient price reaction to the arrival of information and confirms the hypothesis of the rational investor who maximises utility in competitive financial markets [see Copeland and Weston (1988), and LeRoy (1989) for reviews]. That is, prices either follow a random walk or a martingale time series process.

Under a strict interpretation of market efficiency price overreaction and predictable reversions to fundamental value would not be observed. Further, short term speculators would have no influence on price setting, prices will be unaffected by the time horizons of traders, and if prices had 'memories' or some predictable component, then rationally competitive traders would quickly arbitrage away profits.

A study of mean reversion in asset prices and returns is an important aspect of the literature on financial markets because, amongst other things, it challenges the assumption that markets are always 'efficient' and provides a defensible theoretical basis for financial analysts and other market participants to forecast future prices and returns. The occurrence of a mean reversion process requires two events: a deviation of prices away from a 'fundamental value' and a predictable reverting time series trend back to 'fundamentals'.

There are a number of hypotheses about the economic and psychological factors which might cause prices to deviate from their fundamental value and result in price mean reversion and have been reviewed in chapter two. For example, Poterba and Summers (1988) proposed that there was an initial 'bandwagon' effect whereby feedback traders buy stock when the price is in an upward trend and sell stock when it is in a downward trend. Their argument is that the established price trend will continue into the future and it
is similar to the assertion that price deviations are caused by 'noise' traders who follow price fads induced by self-fulfilling expectations [Samuelson (1967), Shiller (1986)]. DeBondt and Thaler (1985, 1987) further suggested that investors systematically overreact to current information. They quote Arrow's comments on the work of Kahneman and Tversky that it: 'typifies very precisely the excessive reaction to current information which seems to characterise all the securities and futures markets' [DeBondt and Thaler (1985, p. 794)]. Eventually the overreaction or price fad is reversed when the market realises that it formed unrealistic expectations of the information releases or price fads. Mean reversion will therefore occur when more efficient traders realise that the fundamental value at time \( t \) \( (FV_t) \) is greater or less than the current stock price \( (P_t) \), with the strength of the mean reversion parameter giving one measure of the arbitrage efficiency of the market.

### 9.2.2 Prior Empirical Research on Security Prices

DeBondt and Thaler (1985) first suggested that if the overreaction of speculators to information releases caused prices to systematically overshoot, then the eventual reversal could be predicted from past return data. They examined monthly return data for portfolios of stocks on the New York Stock Exchange (NYSE) for the period 1926 through 1982, and tested for mean reversion over periods ranging between one to five years. Price returns from portfolios which contained winner and loser stocks were found to be mean reverting. Further, the five year price reversals for the loser portfolios were found to be more pronounced than for winners, and the more extreme were the initial price deviations, the greater were the subsequent reversals. Bremer and Sweeney (1988) used data from the period July 1962 to December 1986, and tested for mean reversion after large one day price jumps of 10% or greater. Their findings were similar to those of the De Bondt and Thaler study - significant price reversion for losers, less significant reversion for winners, and the reversion parameter increasing in strength with the size of the initial price jump. Lehmann (1988) extended the scope of the above studies by including securities listed on both the NYSE and AMEX over the period 1962 through
1986. Lehmann's strategy was to construct a portfolio by buying all stocks that lagged the market during the prior week (losers) and selling short the stocks that led the market (winners). Lehmann found that such a portfolio earned excess returns of 19.4% over six months and that two thirds of the profit was generated by the 'losers'.

Poterba and Summers (1988) applied a variance ratio test to examine changes in volatility over time. The variance model utilises the fact that if the log of stock prices follows a random walk, then the variance of returns should be proportional to the return horizon. They discovered that the variance of eight year price returns was between three and four times the annual variance, when, in fact if the market was efficient, it should have been about eight. They further concluded that the stock market was inefficient since prices exhibited a predictable mean reversion process. Fama and French (1988) adopted a more conventional method by regressing stock returns on past returns to test for mean reversion over long-term periods. They found that there was significant negative autocorrelation in long horizon stock returns and that between 25 and 45 percent of the variation of 3 to 5 year stock returns could be predicted from past returns. Fama and French (1989) later argued that the observed mean reversion behaviour in expected returns to stocks and bonds varied through time in a manner which was consistent with fundamental business conditions. In other words there are time-varying risk premiums.

The contemporary research on mean reversion was recently extended to futures markets by Jackson, Zulauf and Irwin (1992), who studied the price behaviour of corn, soy beans, hogs and fed cattle futures prices over the period 1975 to 1989; and Hodgson, Keef and Okunev (1993) who examined the time series behaviour of the AOI and the associated SPI futures contract prices. Both studies found significant mean reverting behaviour in futures prices with Hodgson, Keef and Okunev reporting stronger mean reversion in futures prices compared to stock prices.

In summary the empirical evidence suggests the following:

(i) prices do not always follow a random walk,

(ii) prices mean revert in a fashion that is predictable from past behaviour,
(iii) mean reversion is stronger for 'loser' portfolios,
(iv) mean reversion increases with the size of the initial price jump, and
(v) mean reversion may be stronger in futures markets.

9.2.3 Futures-Cash Mispricing and the Basis

Futures-Cash Mispricing

A major problem with the above studies is that the long term mean and fundamental value are not necessarily related. However, the existence of a futures contract and an underlying cash market provides a natural economic link, and the fundamental value of the difference between observed futures prices and theoretical prices is zero (see sections 8.2 and 8.3 for a formal analysis). From chapter eight (section 8.3) the theoretical cost of carry relation between the price of the futures and the underlying stock index is given by:

\[ F_{t,T} = I_t e^{(r - d)(T - t)} \]  \hspace{1cm} (9.1)

where \( F_{t,T} \) is the theoretical futures price at time \( t \) for a forward contract expiring at time \( T \), \( I_t \) is the AOI index price at \( t \), \( e \) is the exponential function, \( r(T-t) \) is the yield at time \( t \) of a risk free discount bond maturing at time \( T \), and \( d \) is the continuous dividend yield over time \( t \) to \( T \).

The theoretical mispricing \( M_{t,T} \) is defined by:

\[ M_{t,T} = \ln (F_{t,T}) - \ln (F_{tm,T}) \]  \hspace{1cm} (9.2)

where \( \ln \) is the natural logarithm, \( F_{tm,T} \) is the spot market price at time \( t \) for a forward contract expiring at \( T \), and \( F_{t,T} \) is the theoretical futures price at time \( t \) for a forward contract expiring at forward time \( T \).
Under an arbitrage induced explanation of pricing, the trading activities of stock index arbitrageurs are presumed to drive the elastic realignment of stock index and index futures prices. If the mispricing is greater than zero then arbitrageurs simultaneously sell the index futures and buy the stock index portfolio, pulling the mispricing back to zero. If the mispricing is less than zero then the opposite trading strategy and price reactions occur.

*Basis and Basis Changes*

The stock index basis, \( B_t \), is the difference between the futures price, \( F_t \), and the underlying stock index level, \( S_t \), at a point in time, \( t \),

\[
B_t = F_t - S_t
\]  

(9.3)

In perfectly functioning markets basis changes should be serially uncorrelated. In such a setting, and without loss of generality, \( F_t \) and \( S_t \) can be assumed to follow random walks with homoscedastic increments. Changes in the index level, \( s_t = S_t - S_{t-1} \), and the futures price, \( f_t = F_t - F_{t-1} \), are therefore each serially uncorrelated. Since the basis is the difference between the futures price and the stock index level, it too follows a random walk (albeit of a different error structure) and change in the basis:

\[
b_t = B_t - B_{t-1} = f_t - s_t
\]  

(9.4)

are therefore serially uncorrelated. Again, in a competitive and efficient arbitrage market setting, when the basis widens above or below its theoretical level, arbitrageurs will simultaneously buy/sell index futures and sell/buy the index portfolio. These actions would ensure that changes in the basis are random.

Despite the theoretical predictions induced by arbitrage arguments, a number of empirical studies from different international markets have consistently reported negative first order
autocorrelation in basis and mispricing changes. MacKinlay and Ramaswamy (1988) investigated the mispricing change on 15-minute S&P 500 futures during the period June 1983 through June 1987. They found negative average first order autocorrelation of -0.23, with higher negative autocorrelation later in the sample period, despite an increase in trading activity. Yadav and Pope (1990) used daily closing prices on the FTSE 100 futures and stock index on LIFFE to calculate the basis. Average first order autocorrelation was -0.24 and this increased in more recent years along with stock market trading activity. Lim (1992) extended the analysis to Asian markets by examining 5-minute changes in the basis of the Nikkei 225 index and futures traded on the SIMEX for 20 randomly selected days from the 1988-89 contract period. Lim also found negative first order autocorrelation and that it was largest for the most recent contract.

9.2.4 A Statistical Illusion?

Miller, Muthuswamy and Whaley (1994) proposed an alternative explanation for the observed negative autocorrelation in basis changes - that it is merely a 'statistical illusion' arising because many stocks in the stock index portfolio trade infrequently. They argued that even if arbitrage never occurred, reported basis changes would appear to be negatively autocorrelated as lagged stocks eventually traded and got their prices updated. An example given to illustrate this point was the stock market collapse on Monday, October 19, 1987 when there were heavy imbalances in overnight orders. The futures market opened that day down seven percent, but the reported stock index did not fall immediately because it was based on the last transaction price of each component stock. This meant that the stock index mainly reflected the obsolete prices of Friday's close, not the prices actually achievable at Monday's opening. As each stock traded the reported index level moved closer to the futures price, with the index taking about 90 minutes to revert to equilibrium value.

Miller, Muthuswamy and Whaley (1994) used 15-minute observations from the basis between Standard and Poor's 500 (S&P) and Value Line Composite Index (VLCI) cash
and futures markets for various periods from April 1982 through March 1991 to determine the extent to which the observed negative autocorrelation in the basis could be traced to the actions of index arbitrageurs. They first eliminated all pairs of consecutive price changes during the period 1988 to 1991 in which the theoretical mispricing exceeded 0.25%. Mispricings outside these transaction cost bands were taken as potential arbitrage opportunities. After this filter was applied the autocorrelation dropped only slightly from -0.416 to -0.360. The second test involved an examination of the first order autocorrelation of 15-minute basis changes for the Value Line Composite Index (VLCI). This index is one that cannot be arbitraged because it is geometrically weighted and the possibility of replicating the underlying index is ruled out. The first order autocorrelation of the VLCI basis changes was -0.182. They argued that this behaviour could not be attributed to arbitrage activity. In order to gauge the prevalence of index arbitrage, the trading volume of arbitrage activity was obtained from the NYSE superdot system which records the simultaneous purchase or sale of at least 15 different stocks with a market value of $1 million or more. They found that index arbitrage accounted for about 43% of program trading which is a very small (3.8%) percentage of total trading volume. Finally, Miller, Muthuswamy and Whaley purged the effects of thin trading from the S&P 500 stock index and examined the impact on the first order autocorrelation of the basis. After adjustment, the first order autocorrelation dropped from -0.369 to -0.252. Taken together the evidence implied that formal arbitrage accounted for only a small fraction of daily trading volume and could not fully explain the negative autocorrelation in basis changes. Miller, Muthuswamy and Whaley concluded that the differences in the frequency of trading of individual stocks within stock indexes induced the mean reversion behaviour in the basis.

Yadav and Pope (1993a) analysed and compared the mean reversion properties of the index futures mispricing series by applying the Dickey-Fuller unit root test. They used the 15-minute mispricing series data set calculated by MacKinlay and Ramaswamy (1988) on the S&P 500 index over the period September 1983 to June 1987, to compare with hourly mispricings derived from the FTSE 100 index over the period April 1986 to March
1990. The estimated mean reversion parameter was statistically significant from zero but not very large. On average it was 0.018 in the US and higher at 0.038 in the UK. Mean reversion had a U-shaped pattern over the course of the trading day. It was significantly lower on Mondays, and was higher with decreasing futures contract time to expiration and high levels of mispricing in the previous period.

Yadav and Pope countered the argument of Miller, Muthuswamy and Whalley (1994), that mean reversion was a statistical illusion generated by infrequent trading in index stocks, by running simulations. They concluded that the simulations could generate negative serial correlation in the mispricing series but could not generate mean reversion when defined as the negative dependence of the change in mispricing on the level of mispricing in the previous period. They also argued that empirically observed seasonalities in the mean reversion parameter were opposite to those predicted by explanations based on infrequent trading. For example, mean reversion was an increasing function of the level of mispricing in the previous period (arbitrage induced), mean reversion increased as the time to maturity decreased (decreasing arbitrage risk and time to maturity is not a surrogate for thin trading in stocks), and U-shaped intraday patterns in mean reversion were correlated with trading volume (trading volume is an inverse proxy for infrequent trading).

Yadav and Pope (1993b) also analysed the mean reversion in the time series of spread mispricing. A spread arbitrage is the simultaneous buying and selling of futures contracts with different delivery dates.\(^2\) The analysis of calendar spreads overcomes a number of microstructure impediments inherent in modelling the related cash/futures mispricing series. For example, the behaviour of the spread mispricing should be unrelated to measurement errors such as the infrequent trading effect in the stock index, restrictions on short sales, and execution lag associated with implementing the arbitrage spread. Yadav and Pope found that the absolute value of spread mispricing often exceeded theoretical transaction cost boundaries, there was a high degree of persistence in mispricing, and the

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\(^2\) The analysis of spread mispricing for gold futures contracts in Australia has been analysed by Hodgson and Barrack (1992).
first order autoregressive parameter for the change in mispricing was \(-0.492\). Moreover, trading strategies which incorporated short term spreads, and were triggered by over and under priced far futures contracts, earned significant positive and negative returns.

9.3 MEAN REVERSION MODELS

9.3.1 A Mean Reversion Model

In this section a general mean reversion model which is generated by an Ornstein-Uhlenbeck elastic random walk is first described. This type of process has been used in modelling interest rates by Vasicek (1977) and it provides a flexible technique to model a number of mean reverting processes. In continuous time, mispricing is governed by the following diffusion process:

\[
dM(t) = \beta \left( FV(t) - M(t) \right) dt + \sigma dw(t)
\]  

(9.5)

where

\[
\begin{align*}
dM(t) & \quad \text{is the instantaneous change in mispricing,} \\
\beta & \quad \text{is the speed of adjustment coefficient,} \\
FV(t) & \quad \text{is the theoretical fundamental value,} \\
M(t) & \quad \text{is the observed mispricing at time } t, \\
w(t) & \quad \text{is a standard Wiener process}^3, \\
\sigma^2 & \quad \text{is the variance of } dM(t) \text{ per unit time, and} \\
dt & \quad \text{is the time interval between observations.}
\end{align*}
\]

The diffusion process of equation (9.5) permits numerous possibilities. For example, if \(0 < \beta < 2\) then the process is mean reverting and if \(\beta\) lies outside this range then the process is unstable. If \(0 < \beta < 1\) then adjustments in \(M(t)\) will revert to the mean, and if 1

\(^3\) A standard Wiener process has a mean zero and unit variance. For an introduction to Wiener processes, see Karlin and Taylor (1975, p.22).
< \beta < 2$, then adjustments in $M(t)$ will overshoot the mean, but the process will still be stable. Finally, if $\beta = 0$, then equation (9.5) simply becomes a white noise process.

For the specific case where $\beta > 0$ and $M(t) > FV(t)$ the expected change in the mispricing will be negative. Similarly if $FV(t) - M(t) > 0$, then the expectation is that $dM(t) > 0$ and the process will always revert back towards the fundamental value. The discrete time version of equation (9.5) is given by:

$$\Delta M = \beta(FV - M) \Delta t + \sigma \Delta w$$

or

$$\Delta M = \beta FV \Delta t - \beta M \Delta t + \sigma \Delta w$$

Equation (9.7) suggests the following regression relationship:

$$\Delta M(t) = \gamma_0 + \gamma_1 M(t) + e(t)$$

where:

$$\gamma_1 = - \beta \Delta t \Rightarrow \beta = \frac{-\gamma_1}{\Delta t},$$

$$\gamma_0 = \beta FV \Delta t \Rightarrow FV = \frac{\gamma_0}{\beta \Delta t} = - \frac{\gamma_0}{\gamma_1},$$

$e(t)$ = the residual term,

$\text{var } e(t) = \sigma^2$, and

$\Delta M(t) = M(t+1) - M(t)$

Equation (9.8) can also be written as:

$$M(t+1) = \gamma_0 + (1 + \gamma_1) M(t) + e(t)$$

(9.8a)

and if $\gamma_1 = 0$ then this implies a unit root and nonstationarity in the data with no mean reversion.
As stated earlier, $\beta$ is the speed of adjustment coefficient which is a measure of the strength of the mean reversion process. A value of $\beta$ close to one would indicate strong mean reversion and a value of $\beta$ close to zero would imply weak mean reversion. In the above model the fundamental value (FV) or the long-term mean is estimated from the two parameters, $\gamma_0$ and $\gamma_1$ in the regression equation. The model can be made more flexible by introducing the possibility of exponential growth in the long term mean as follows:

$$dM = \beta (FVe^{kt} - M(t)) \, dt + \sigma dw(t)$$

(9.11)

For exponential decay, the model becomes:

$$dM = \beta (FVe^{-kt} - M(t)) \, dt + \sigma dw(t)$$

(9.12)

While the Ornstein-Uhlenbeck process forms the basis of a test for mean reversion it is somewhat restrictive. It, however, can be used as a foundation to develop statistical models which are more representative of the underlying structure of the market. One such statistical model is developed in the following section.

### 9.3.2 Statistical Testing of Mean Reversion

The basic statistical model applied in this chapter is:

$$\Delta M_t = \phi M_{t-1} + \gamma_0 + \sum_{j=1}^{p} \lambda_j \Delta M_{t-j} + \nu_t$$

(9.13)

where:

- $\phi$ is the mean reversion parameter,
- $M_0$ is equal to $M_t - M_{t-1}$,
- $\sum_{j=1}^{p} \lambda_j \Delta M_{t-j}$, $j = 1, ..., p$ are the lagged changes in mispricing
- $\gamma_0$ is the intercept term, and
- $\nu_t$ is the error term.
For this model the *augmented Dickey-Fuller test* developed by Dickey and Fuller (1979, 1981), described in Greene (1993, pp.563-566) and applied by Yadav and Pope (1993a), is used to test that the mean reversion parameter ($\phi$) is equal to zero. This is equivalent to testing for the presence of unit roots in futures mispricing. The augmented Dickey-Fuller procedure has a number of statistical advantages in testing for mean reversion in a mispricing series. First, $\phi$ is a measure of the mean reversion of the series back to a *stationary* model. Secondly, Dickey and Fuller (1976) showed that the estimator $\phi$ was biased downwards as it approached zero. The conventional t-test tends, incorrectly, to reject the hypothesis that $\phi$ equals zero. The practical solution to this problem devised by Dickey and Fuller was to derive an appropriate set of critical values for testing the hypothesis that $\phi$ equals zero. In the application of the model (in later sections of this chapter) the hypothesis that $\phi$ is equal to zero is tested against the revised set of critical values for the modified $\tau_u$ statistic described in Fuller (1976).

The intercept term ($\gamma_0$) is included in equation (9.13) in order to capture any significant deviations from the fundamental value after the modelling process. However, in all further empirical tests which utilised the full data set, the intercept term was found to be statistically insignificant. Therefore, the intercept term was dropped from any subsequent modelling. The lagged terms in mispricing changes $\Delta M_{t-j}$ ($j = 1, 2, ...p$) are added in order to ensure that the estimate of $\phi$ reflects only the dependence on the level of mispricing in the previous period. As shown in Table 9.1, there is high negative serial correlation in mispricing changes which persists over the entire sample [consistent with the findings of MacKinlay and Ramaswamy (1988) for US and Yadav and Pope (1990) for UK data]. Consequently, in the empirical tests, lagged terms are added up to 42 lags (in order to capture at least two prior days trading). Any nonsignificant autoregressive parameters are then removed in order of least significance until the

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4 A deterministic time trend model in the form $\Delta M_t = \phi M_{t-1} + \alpha (T-t) + \gamma_0 + \sum_{j=1}^{p} \lambda_j \Delta M_{t-j} + \nu_t$ was also applied but the time trend was not found to be significant. See also section 9.4.3.

5 A fundamental value of zero for the mispricing series makes economic sense and lends support to the notion that the cost of carry model (see equations 9.1 and 9.2) is an appropriate model in the *longer* term.
estimated regression residuals ($v_t$) are purged of any significant serial correlation. In all tests this procedure was continued until the Box-Pierce Q-statistic was statistically insignificant up to 42 lags, and the appropriate lags chosen so as to minimise the Schwarz Bayesian Criteria [Schwarz (1978)].

9.4 EMPIRICAL RESULTS

9.4.1 Mispricing Changes

The data set used is the mispricing series described in chapter eight along with the corresponding AOI and SPI return series. Table 9.1 presents a range of sample information on the observed moments of AOI and SPI price changes and the change in the theoretical arbitrage mispricing over the research period. Several points are noteworthy. The 15-minute price changes show significant positive first order autocorrelation for the AOI of 0.238 which is higher than the 0.128 observed for 15-minute changes in the S&P by Miller, Muthuswamy and Whaley (1994). This time series behaviour traces to infrequent trading of some index stocks and confirms the hypothesis that the Australian market is more thinly traded than the US market. The 15-minute price changes in the SPI futures contract shows negative and comparably smaller autocorrelation. For the SPI series over the entire year, the first order autocorrelation is -0.038 which is comparable to the -0.029 observed by Miller, Muthuswamy and Whaley (1994) and reflects a narrow bid-ask spread in the SPI.

Table 9.1 also details persistent negative first order autocorrelation in the theoretical mispricing changes. The autocorrelation is -0.344 for the full sample period and is consistently high and negative over all the contract periods. One other observation is that the strength of the negative first order autocorrelation in the mispricing series does not appear to depend on the level of positive autocorrelation (a proxy for infrequent trading) in the stock index. For example, the highest negative autocorrelation in the mispricing changes series (-0.414) during the March 1993 period is associated with the lowest

---

6 Miller, Muthuswamy and Whaley (1994, pp.493-494) provide a detailed discussion on this point.
autocorrelation in the AOI (0.124). This behaviour is opposite to that predicted by the hypothesis that mean reversion in stock-futures mispricing is caused by thin trading in the underlying stocks. Finally, the level of the negative first order autocorrelation in the SPI mispricing changes is very similar to that observed by Miller, Muthuswamy and Whaley (1994) for the S&P mispricing changes (-0.360) and S&P basis changes (-0.416). This is the case even though the S&P index price returns have significantly lower first order autocorrelation when compared to the Australian AOI.

Table 9.1

<table>
<thead>
<tr>
<th>Period</th>
<th>No of observations</th>
<th>( \hat{\rho}_1(f^o) )</th>
<th>( \hat{\rho}_1(s^o) )</th>
<th>( \hat{\rho}_1(m^o) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Begins</td>
<td>Ends</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4/92</td>
<td>3/93</td>
<td>5009</td>
<td>-0.038</td>
<td>0.238</td>
</tr>
<tr>
<td>4/92</td>
<td>6/92</td>
<td>1240</td>
<td>-0.075</td>
<td>0.261</td>
</tr>
<tr>
<td>7/92</td>
<td>9/92</td>
<td>1289</td>
<td>0.045</td>
<td>0.329</td>
</tr>
<tr>
<td>10/92</td>
<td>12/92</td>
<td>1240</td>
<td>0.024</td>
<td>0.322</td>
</tr>
<tr>
<td>1/93</td>
<td>3/93</td>
<td>1240</td>
<td>-0.127</td>
<td>0.124</td>
</tr>
</tbody>
</table>

Estimated first-order autocorrelation (\( \hat{\rho}_1 \)) of observed SPI futures price changes (\( f^o \)), AOI stock price changes (\( s^o \)), and changes in the theoretical mispricing between the AOI and SPI (\( m^o \)) over 15-minute intervals. The exceptions are 1000 which is an overnight interval and 1400 which is a 90-minute interval. The sample period extends from 1 April 1992 through 30 March 1993. The table decomposes the analysis to match the futures contract periods expiring in June, September and December 1992 and March 1993.

9.4.2 Mean Reversion

The model outlined in equation (9.13) is estimated separately to the mispricing series previously described in chapter eight for the full period and the four contract periods over the year April 1992 through March 1993. The following null hypothesis is tested:

\[
\text{Ho} : \phi = 0 \quad \text{against the alternative that} \quad \phi > 0. 
\]

Table 9.2 reports the results of the unit root tests for the Australian mispricing series. The null hypothesis of a unit root is rejected for the full data set and for each contract period. Standard residual analysis indicated that the model was a good fit with the residuals normally distributed and the Durbin-Watson statistic showed that there was
insignificant first order autocorrelation. Table 9.2, therefore, establishes the existence of mean reversion in the Australian market that is negatively related to the level of mispricing in the previous period and is consistent across futures contract periods. These findings are generally consistent with the results of Yadav and Pope (1993a) in the case of US data. In a well functioning security market one would expect that arbitrage opportunities would be rapidly eliminated and the mean reversion parameter should be large as well as significant. The size of the average mean reversion parameter is, however, relatively small at 0.0269 but larger than the observed average mean reversion parameter of 0.018 for the US and smaller than the overall mean reversion parameter of 0.038 in the UK [Yadav and Pope (1993a)]. In Australia it takes approximately thirty seven periods, or almost two days, for the mispricing to revert to the fundamental value. The fundamental value calculated from equation (9.10) is approximately 0.0003848 with a t-value of 0.37.

### Table 9.2

**MEAN REVERSION IN SPI INDEX FUTURES MISPRICING 15-MINUTE OBSERVATIONS - 1 APRIL 1992 to 30 MARCH 1993**

<table>
<thead>
<tr>
<th>Time period</th>
<th>Mean Reversion Parameter ((\phi))</th>
<th>Standard Error</th>
<th>(\tau_u) Statistic # null (\phi = 0)</th>
<th>Q Statistic +</th>
</tr>
</thead>
<tbody>
<tr>
<td>4/92 to 3/93 (1)</td>
<td>0.0269</td>
<td>0.00327</td>
<td>8.23***</td>
<td>0.946</td>
</tr>
<tr>
<td>4/92 to 6/92 (2)</td>
<td>0.0284</td>
<td>0.00678</td>
<td>4.19***</td>
<td>0.900</td>
</tr>
<tr>
<td>7/92 to 9/92 (3)</td>
<td>0.0716</td>
<td>0.01051</td>
<td>6.82***</td>
<td>0.427</td>
</tr>
<tr>
<td>10/92 to 12/92 (4)</td>
<td>0.0289</td>
<td>0.00663</td>
<td>4.36***</td>
<td>0.640</td>
</tr>
<tr>
<td>1/93 to 3/93 (5)</td>
<td>0.0344</td>
<td>0.00742</td>
<td>4.64***</td>
<td>0.806</td>
</tr>
</tbody>
</table>

(1) R-squared: 0.1167, Durbin-Watson: 1.998
(2) R-squared: 0.1402, Durbin-Watson: 2.001
(3) R-squared: 0.1097, Durbin-Watson: 2.016
(4) R-squared: 0.0950, Durbin-Watson: 2.013
(5) R-squared: 0.1673, Durbin-Watson: 1.999

+ P-value of Box-Pierce Q statistic at lag 42

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

# \(H_0: \phi = 0\) against the alternative that \(\phi\) is greater than zero, tested using the Fuller (1976) \(\tau_u\) statistic.

7 The mean reversion periods examined were 15-minutes in the US and 1-hour in the UK.
8 For all other models applied in this chapter the \(\gamma_0\) parameter is very similar to the one derived from the above model and not significantly different from zero. Consequently, the \(\gamma_0\) parameter is not reported for any subsequent models.
An inspection of the mean reversion parameter by futures contract period shows there is stronger mean reversion (0.0716) during the September 1992 contract. The statistical illusion hypothesis predicts that this period should have the highest level of nontrading in the stock index. Table 9.1 reveals that this period has the highest level of positive first order autocorrelation in the AOI (0.329), but that the following period has a similar level but with a much lower mean reversion parameter. The September quarter period is traditionally the financial reporting season in Australia and the positive first order autocorrelation may be induced by the reaction of traders to the release of that information [DeBont and Thaler (1989), Poterba and Summers (1988), Froot, Scharfstein and Stein (1992)]. This contention is supported by the positive autocorrelation in the SPI during the September contract.

At this general stage the evidence could support an arbitrage induced hypothesis (the mean reversion parameter is significant), or a statistical illusion hypothesis (the mean reversion parameter is small and is higher in Australia because of the higher positive first order autocorrelation caused by nontrading in the component underlying stocks). Some further tests similar to Yadav and Pope (1993a) are now applied to examine the mean reversion parameter as a function of time to contract expiration, transaction cost bounds, and intraweek and intraday seasonality. Other tests are added in order to examine mean reversion during bull and bear trading days and the impact of unexpected trading volume.

9.4.3 Time to Maturity and Mean Reversion

The testing of mean reversion as time to maturity of the futures contract decreases, can potentially throw some light on the debate about whether mean reversion in mispricing is caused by arbitrageurs or is a 'statistical illusion'. If the uncertainty about future dividends and interest rates increases monotonically with the time to maturity, then the risks associated with arbitrage should increase likewise. The arbitrage induced theory of mean reversion predicts that mean reversion will decline monotonically with an increase in average time to maturity of the futures contract.
Secondly, under the cost of carry pricing formula (9.1) the mispricing will deterministically converge to zero at maturity, implying that the change in mispricing with the time to maturity of the futures contract will have a negative first order serial dependence. The level of that dependence for 15-minute observations in the Australian market, however, is very small and is in the order of -0.00055. Therefore, if infrequent trading in ADI stocks is not associated with time to maturity of the futures contract, then the 'statistical illusion' hypothesis predicts that there will only be a slight negative autocorrelation pattern in the mean reversion parameter as a function of declining time to maturity. The variation of the mean reversion parameter \( \phi_c \) with time to maturity of the futures contract is estimated using the following model:

\[
\Delta M_t = \sum_{c=1}^{6} \phi_c D_c M_{t-1} + \sum_{j=1}^{p} \lambda_j \Delta M_{t-j} + \nu_t \tag{9.14}
\]

where \( \phi_c \) is the mean reversion parameter,

\( \Delta M_t \) is equal to \( M_t - M_{t-1} \),

\[
\sum_{j=1}^{p} \lambda_j \Delta M_{t-j}, \quad j = 1, \ldots, p \quad \text{are the lagged changes in mispricing}
\]

\( \nu_t \) is the error term, and

\( D_c \) is equal to one if time to maturity for the futures contract \( (T - t) \) lies within the window \( c \) and zero otherwise.

The futures contract time to maturity windows are defined as follows:

\[
\begin{align*}
\text{c = 1} : & \quad (0 \text{ days} \leq (T - t) \leq 15 \text{ days}) \\
\text{c = 2} : & \quad (16 \text{ days} \leq (T - t) \leq 30 \text{ days}) \\
\text{c = 3} : & \quad (31 \text{ days} \leq (T - t) \leq 45 \text{ days}) \\
\text{c = 4} : & \quad (46 \text{ days} \leq (T - t) \leq 60 \text{ days}) \\
\text{c = 5} : & \quad (61 \text{ days} \leq (T - t) \leq 75 \text{ days}) \\
\text{c = 6} : & \quad (76 \text{ days} \leq (T - t) \leq 90 \text{ days})
\end{align*}
\]

9 This is calculated as \([1/T]\) where T is the number of time intervals remaining in the futures contract. In the case of a 90 day futures contract with twenty 15-minute intervals in the trading day, this is equal to \( 1/1800 \) [Miller, Muthuswamy and Whaley (1994, footnote 2)].
The results in Table 9.3 show that there is no strongly distinct pattern, such as increasing or decreasing mean reversion with time to maturity. The mean reversion parameter is significant for all time periods, it is highest for the period close to maturity (0-15 days), and the hypothesis that $\phi_c (c = 1, 2, 3, 4, 5, 6)$ are equal is not rejected by the F statistic. This result differs somewhat from the findings of Yadav and Pope (1993a), who generally observed declining mean reversion with increasing time to maturity, and a mean reversion parameter insignificantly different from zero in excess of 75 days to maturity.

In Australia, the evidence suggests that the risk of arbitrage is not related to the time period of the futures contract. This may be related to the fact that dividend payments are primarily disbursed in the September quarter and therefore uncertainty of payment is confined to this contract.

<table>
<thead>
<tr>
<th>Time to Maturity Window</th>
<th>Mean Reversion Parameter ($\phi_c$)</th>
<th>Standard Error</th>
<th>$\tau_u$ Statistic $H_{c1}$</th>
<th>F Statistic $H_{c2}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-15 days (1)</td>
<td>0.0398</td>
<td>0.01159</td>
<td>3.43***</td>
<td>0.68</td>
</tr>
<tr>
<td>16-30 days (2)</td>
<td>0.0200</td>
<td>0.00698</td>
<td>2.87**</td>
<td></td>
</tr>
<tr>
<td>31-45 days (3)</td>
<td>0.0276</td>
<td>0.00776</td>
<td>3.56***</td>
<td></td>
</tr>
<tr>
<td>46-60 days (4)</td>
<td>0.0271</td>
<td>0.00771</td>
<td>3.52***</td>
<td></td>
</tr>
<tr>
<td>61-75 days (5)</td>
<td>0.0380</td>
<td>0.00976</td>
<td>3.89***</td>
<td></td>
</tr>
<tr>
<td>76-90 days (6)</td>
<td>0.0234</td>
<td>0.00690</td>
<td>3.39***</td>
<td></td>
</tr>
</tbody>
</table>

R-squared 0.1173, Durbin-Watson 1.998

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

$H_{c1}$: $\phi_c = 0$ against the alternative that $\phi_c$ is greater than zero; $c = 1, 2, 3, 4, 5, 6$; tested using the Fuller (1976) $\tau_u$ statistic.

$H_{c2}$: $\phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi_5 = \phi_6$ against the alternative that at least one coefficient is different.
9.4.4 Day of the Week and Mean Reversion

Previous research has shown a day of the week effect in security markets. In the US, stock market returns on Monday are the lowest of the week and significantly negative [French (1980), Gibbons and Hess (1981)]. In Australia, there is a weak Monday effect but in general Tuesday returns are the lowest of the week [Ball and Bowers (1988), Easton and Faff (1991)]. There is also evidence that trading volume is lower on Monday compared to other days of the week [Gerety and Mulherin (1992), Goodhart and Thompson (1988)]. Given that Monday is a more 'subdued' trading day it is of interest to test if arbitrage activity, proxied by the mean reversion parameter, is affected by the lower trading volume on Monday or the negative price return (the bear market effect) on Tuesday. The model tested was:

$$\Delta M_t = \sum_{d=1}^{5} \phi_d D_d t_{t-1} + \sum_{j=1}^{p} \lambda_j \Delta M_{t-j} + \nu_t$$

(9.15)

where $D_d$ are dummy variables that take the value of one and zero. In the above model $d = 1, 2, 3, 4$ and 5 correspond to Mondays, Tuesdays, Wednesdays, Thursdays and Fridays. Other terms in the model are as previously defined. The results are reported in Table 9.4.

All mean reversion parameters are significant at the 1% level. The lowest mean reversion occurs on Monday, the highest on Tuesday, and there is a general declining trend after the peak on Tuesday ($\phi_2 > \phi_3 > \phi_4 > \phi_5$). The F statistic, which tests for the equality of the Monday mean reversion parameter against the remainder of the week mean reversion parameter ($H_{d2}$), is significant at the 10% level. These results are similar to those in the US which report a low mean reversion on Monday with the highest on Tuesday, and the UK which reports low mean reversion on Monday and high mean reversion on Wednesday [Yadav and Pope (1993a)]. They add support for a low Monday mean reversion phenomenon and raise the possibility that arbitrageurs are less active on Monday.
Table 9.4
MEAN REVERSION IN SPI INDEX FUTURES
MISPRICING - DAY OF THE WEEK EFFECT

Unconditional Least Squares Estimation

<table>
<thead>
<tr>
<th>Day of the Week</th>
<th>Mean Reversion Parameter ($\phi_d$)</th>
<th>Standard Error</th>
<th>$\tau_d$ Statistic $H_{d1}$</th>
<th>F Statistic $H_{d2}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>0.0193</td>
<td>0.00573</td>
<td>3.37***</td>
<td>3.40*</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.0385</td>
<td>0.00636</td>
<td>6.06***</td>
<td></td>
</tr>
<tr>
<td>Wednesday</td>
<td>0.0332</td>
<td>0.00666</td>
<td>4.99***</td>
<td></td>
</tr>
<tr>
<td>Thursday</td>
<td>0.0276</td>
<td>0.00591</td>
<td>4.67***</td>
<td></td>
</tr>
<tr>
<td>Friday</td>
<td>0.0274</td>
<td>0.00670</td>
<td>4.09***</td>
<td></td>
</tr>
</tbody>
</table>

R-squared 0.1178  Durbin-Watson 1.998
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

$H_{d1}$:  $\phi_d = 0$ against the alternative that $\phi_d$ is greater than zero; $d = 1, 2, 3, 4, 5$; tested using the Fuller (1976) $\tau_d$ statistic.

$H_{d2}$:  $\phi_I = \phi_w$ against the alternative that $\phi_I$ is not equal to the mean reversion during Tuesday, Wednesday, Thursday and Friday (i.e. $w$ is the day of the week other than Monday).

The low mean reversion on Monday, however, does not appear to depend upon low or negative daily returns. In the US there is a Monday negative return effect and in Australia negative returns are more likely to occur on Tuesday. But the mean reversion parameter is highest in Australia on Tuesday. An alternate explanation is that low mean reversion is related to low trading volumes. In chapter three it was observed that there was lower trading volume on Mondays. Some further tests are constructed and applied later in this chapter in order to examine the impact of unexpected changes in trading volume on the mean reversion parameter.

9.4.5 Transaction Costs and Mean Reversion

The hypothesis that transaction costs have an impact on arbitrage related activity is important to the debate in this area. Under the arbitrage induced theory the potential explanatory power of the mean reversion parameter is related to the different levels of marginal transaction costs faced by arbitrageurs. For example, the mean reversion parameter is predicted to be zero if mispricing in the previous period is smaller than the
transaction cost of the lowest cost arbitrageur. Arbitrage activity would progressively increase in magnitude as mispricing crosses the transaction costs thresholds of the different categories of arbitrageurs. The mean reversion parameter should then follow a V-shaped pattern around the fundamental value of zero as mispricing progressively deviates from zero and attracts greater numbers of arbitrageurs.

The potential explanatory power of the mean reversion parameter should, ideally, be related to the different marginal transaction costs faced by arbitrageurs. A consummate test would be to identify variations in the mean reversion parameter by aligning the previous period's mispricing to transaction cost bands in accordance with different arbitrage cost thresholds. Unfortunately, this is conceptually difficult because of a number of practical considerations which mean that different participants face varying costs. For example:

(i) The transaction costs of arbitrageurs will vary across different participants usually as an increasing cost function from brokers, to institutions, through to small investors.

(ii) Some arbitrageurs have marginal costs which are confined to transactions in the futures market. For example, arbitrageurs with existing positions who exercise the rollover or early unwinding option, or who use the futures market as an intermediary market to the stock market fall in this category.

(iii) Arbitrageurs who initiate new hedge positions are required to incur transaction costs in both the stock and futures markets.

In prior research on stock index arbitrage a wide range of transaction cost windows has been applied. In the US, MacKinlay and Ramaswamy (1988) used an estimate of 0.5%, Neal (1992) estimated transaction costs of index arbitrage programs at 0.31%, and Miller, Muthuswamy and Whaley (1994) used 0.25% as a conservative cost window. In the UK, Yadav and Pope (1992) estimated transaction costs of futures only arbitrage at 0.25% and round trip full stock-futures arbitrage at 0.75%. In Australia, Hodgson, Kendig and Tahir (1993), estimated full stock-futures arbitrage transaction costs at about 0.70%, with futures only costs at less than 0.20%. In order to concede the presence of a
hierarchy of different categories of arbitrage transaction costs, and to approximate previous research, seven transaction cost windows as defined below were allowed. Similar to the previous sections the following model was then applied to test the mean reversion parameter against the value of the previous period's mispricing.

$$\Delta M_t = \sum_{w=1}^{7} \phi_w D_w M_{t-1} + \sum_{j=1}^{\gamma} \lambda_j \Delta M_{t-j} + \nu_t \quad (9.16)$$

where $D_w$ is equal to one if the previous mispricing lies within the lagged mispricing window $(w)$ and zero otherwise. The lagged mispricing windows were defined as follows:

- $w = 1 : (M_{t-1} > 0.75\%)$
- $w = 2 : (0.50\% < M_{t-1} \leq 0.75\%)$
- $w = 3 : (0.25\% < M_{t-1} \leq 0.50\%)$
- $w = 4 : (-0.25\% < M_{t-1} \leq 0.25\%)$
- $w = 5 : (-0.5\% < M_{t-1} \leq -0.25\%)$
- $w = 6 : (-0.75\% < M_{t-1} \leq -0.50\%)$
- $w = 7 : (M_{t-1} < -0.75\%)$

The results are reported in Table 9.5. The arbitrage induced hypothesis predicts that: i) the mean reversion parameter will be zero if the previous period's mispricing is between unprofitable arbitrage transaction cost bounds, and ii) the mean reversion parameter would be an increasing function associated with the increasing mispricing bands. Table 9.5 reveals a flat U-shaped mean reversion pattern across transaction cost windows. Mean reversion is not significantly different from zero in the five innermost lagged mispricing windows which correspond with transaction costs of up to 0.75%. The F-statistic which tests the null hypothesis that the two outermost transaction cost windows (>0.75% and <-0.75%) are significantly different from the inner five windows, is significant at the 5% level (F-statistic = 3.68).
### Table 9.5

**MEAN REVERSION IN SPI INDEX FUTURES MISPRICING - PREVIOUS PERIOD'S MISPRICING WITHIN TRANSACTION COST WINDOWS**

<table>
<thead>
<tr>
<th>Lagged Mispricing Window</th>
<th>Mean Reversion Parameter ($\phi_w$)</th>
<th>Standard Error</th>
<th>$\tau_u$ Statistic $H_{1w}$</th>
<th>F Statistic $H_{2w}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_{t-1} &gt; 0.75%$</td>
<td>0.0383</td>
<td>0.0067</td>
<td>5.70***</td>
<td>3.68**</td>
</tr>
<tr>
<td>$0.5% &lt; M_{t-1} \leq 0.75%$</td>
<td>0.0170</td>
<td>0.0094</td>
<td>1.80</td>
<td></td>
</tr>
<tr>
<td>$0.25% &lt; M_{t-1} \leq 0.50%$</td>
<td>0.0062</td>
<td>0.0134</td>
<td>0.46</td>
<td></td>
</tr>
<tr>
<td>$-0.25% &lt; M_{t-1} \leq 0.25%$</td>
<td>0.0263</td>
<td>0.0204</td>
<td>1.29</td>
<td></td>
</tr>
<tr>
<td>$-0.50% &lt; M_{t-1} \leq -0.25%$</td>
<td>0.0045</td>
<td>0.0134</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>$-0.75% &lt; M_{t-1} \leq -0.50%$</td>
<td>0.0175</td>
<td>0.0090</td>
<td>1.94</td>
<td></td>
</tr>
<tr>
<td>$M_{t-1} &lt; -0.75%$</td>
<td>0.0264</td>
<td>0.0062</td>
<td>4.24***</td>
<td></td>
</tr>
</tbody>
</table>

R-squared 0.1179, Durbin-Watson 1.999

*** Significant at the 1% level
**  Significant at the 5% level
*  Significant at the 10% level

$H_{1w}$: $\phi_w = 0$ against the alternative that $\phi_w$ is greater than zero; $w = 1, 2, 3, 4, 5, 6, 7$; tested using the Fuller (1976) $\tau_u$ statistic.

$H_{2w}$: $\phi_1 = \phi_7 = \phi_w$ where $\phi_w$ is the mean reversion over the inner five transaction cost windows against the alternative that $\phi_1 \neq \phi_7 \neq \phi_w$.

Overall the results are similar to the UK and the US results except that the mean reversion parameters in Australia are lower within the inner transaction bounds and are not significant until the 0.75% transaction cost bands are breached. This suggests a number of scenarios: (i) mean reversion only occurs when the value of the previous period's mispricing corresponds to transaction windows where arbitrage is likely to be profitable, (ii) transaction costs for Australian arbitrageurs are significantly higher than those in the US, and (iii) arbitrage activity is more subdued for low cost arbitrageurs. In general, the empirical results are consistent with the hypothesis that mean reversion depends on the value of mispricing in the previous period, and since the mispricing level was classified according to approximate transaction cost levels, mean reversion is associated with arbitrage activity.
9.4.6 Intraday Seasonality in Mean Reversion

Chapters four, five and six document intraday patterns in AOI and SPI returns, trading volume and volatility. In particular there are positive and high returns at the beginning and end of the day, negative return spikes at 1015 and 1430, and higher volatility in the first 30 minutes of morning trading. Further, there is a distinct U-shaped pattern in futures trading volume with clustering of trading at opening and closing.

An empirical examination of the intraday behaviour of mean reversion can shed some light on the proposed explanatory theories. If the 'statistical illusion' proposal is driving mean reversion in mispricing, and if trading volume is an inverse proxy for infrequent trading, then periods of infrequent trading when there is slower activity in the component stocks, should be associated with higher mean reversion. Conversely, periods of high trading volume should be associated with lower mean reversion. On the other hand, if arbitrage is driving mean reversion then we would expect higher mean reversion in periods when arbitrageurs are more active (ie. in periods of high trading volume). Furthermore, if arbitrage activity is an inverse function of risk then the mean reversion parameter should be lower when there is higher volatility in cash and futures prices.

These propositions are examined by applying the following model:

\[ \Delta M_t = \sum_{i=1}^{5} \phi_i D_M t-1 + \sum_{j=1}^{p} \lambda_j \Delta M_{t-j} + v_t \]  (9.17)

where \( D_t \) is equal to one if the previous mispricing lies within the lagged intraday mispricing window \( i, i = 1, \ldots, 5 \) and zero otherwise. These intraday intervals are split into five intervals as indicated below and the results reported in Table 9.6.

- \( i = 1 \) : \( (1600 \leq i \leq 1030) \)
- \( i = 2 \) : \( (1045 \leq i \leq 1130) \)
- \( i = 3 \) : \( (1145 \leq i \leq 1230) \)
- \( i = 4 \) : \( (1400 \leq i \leq 1445) \)
- \( i = 5 \) : \( (1500 \leq i \leq 1545) \)
Table 9.6
MEAN REVERSION IN SPI INDEX FUTURES MISPRICING - INTRADAY PATTERNS

<table>
<thead>
<tr>
<th>Hour of the Day</th>
<th>Mean Reversion Parameter ($\phi_i$)</th>
<th>Standard Error</th>
<th>$\tau_u$ Statistic $H_{1i}$</th>
<th>F Statistic $H_{2i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1600-1030 (1)</td>
<td>0.0525</td>
<td>0.01808</td>
<td>2.90**</td>
<td>7.23***</td>
</tr>
<tr>
<td>1045-1130 (2)</td>
<td>0.0061</td>
<td>0.01745</td>
<td>0.35</td>
<td></td>
</tr>
<tr>
<td>1145-1230 (2)</td>
<td>0.0116</td>
<td>0.01667</td>
<td>0.69</td>
<td></td>
</tr>
<tr>
<td>1400-1445 (1)</td>
<td>0.0424</td>
<td>0.01712</td>
<td>2.48*</td>
<td></td>
</tr>
<tr>
<td>1500-1545 (2)</td>
<td>0.0241</td>
<td>0.01780</td>
<td>1.35</td>
<td></td>
</tr>
</tbody>
</table>

R-squared = 0.1128, Durbin-Watson = 1.998

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

$H_{1i}$: $\phi_i = 0$ against the alternative that $\phi_i$ is greater than zero; $i = 1, 2, 3, 4, 5$; tested using the Fuller (1976) $\tau_u$ statistic.

$H_{2i}$: $\phi_1 = \phi_2$ tests whether the mean reversion after trading halts is equal to the mean reversion from other times of the day against the alternative that $\phi_1 \neq \phi_2$.

The mean reversion pattern over the trading day resembles a humped L-shaped pattern. There is higher, and significant, mean reversion during the first hour of trading, mean reversion is not significantly different from zero during the second and third trading hours and is higher and statistically significant during the hour after lunch but declines towards the close of trading. Again the results support the intraday patterns observed in the mean reversion parameters in the US and UK markets by Yadav and Pope (1993a) with one difference. That is mean reversion in Australia is highest at the resumption of trading after the two trading halts\(^{10}\) - overnight and lunchtime - and this is confirmed by the F-test (7.23) which is significant at the 1% level.

In order to analyse the microstructure of arbitrage activity during these periods the mean reversion across 15-minute intervals was also analysed. It was found that the highest mean reversion parameters were 0.167 at 1015, followed by 0.061 at 1030 and 0.054 at 1430. It might be logical to expect that mean reversion would be highest overnight given that arbitrageurs have the overnight break in which to absorb the implications of the previous day's trading, overnight public information, and to re-evaluate their trading

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\(^{10}\) Only one (overnight) trading halt occurs in the US and UK futures market.
strategies. Higher overnight mean reversion occurs in the US and the UK but this is not the case in Australia where the overnight mean reversion parameter is 0.034. However, it should be borne in mind that in order to obtain a mean reversion process there must be a deviation from the fundamental value. The higher mean reversion parameters in Australia occur at, or subsequent to, the positive and negative return spikes identified in chapter four. It may be that the uncertainty induced around this period by the bunched arrival of overnight information, and the apparent overreaction in the individual stock and futures return series are countered somewhat by the actions of arbitrageurs.

The stronger mean reversion in these periods may also be driven by higher lagged mispricing at that time. An examination of the intraday mispricing levels (see Table 8.1 Chapter 8), shows that mispricing is evenly spread over the trading day with a fairly constant standard deviation. It is, therefore, unlikely that this factor is an acceptable explanation. A more plausible explanation may be that the strength of mean reversion is related to futures trading volume which follows a U-shaped pattern over the trading day (see Chapter five). Further, the day of the week analysis reveals that mean reversion is lowest on Mondays which has a slightly lower trading volume in the futures market. Again, these results are similar to those observed in the UK and US by Yadav and Pope (1993a, p.27) who state that: 'to the extent that trading volume is an inverse proxy for infrequent trading, the [intraday] seasonality in the mean reversion parameter is opposite to that predicted by infrequent trading based explanations.' The impact that surprises in trading volume have on the mean reversion parameter is examined in the next section.

9.4.7 Mean Reversion and Surprises in Trading Activity

Rutledge (1986) proposed that variations in trading volume in futures markets were a proxy for variations in speculative activity, and Miller, Muthuswamy and Whaley (1994) reported that only about 4% of transactions were associated with arbitrage activity. On the other hand, Bessembinder and Seguin (1993) argued that an increase in trading volume which increases open interest may be a proxy for hedging activity. If this is the
case then the strength of the mean reversion parameter should be greater in times of increased trading. Conversely, if increased trading volume is caused by an influx of speculators or noise traders, then arbitrage activity may be overwhelmed by speculative trading and the mean reversion parameter would be weaker. Therefore, under the speculative trading hypothesis, mean reversion would be lower during periods of increased trading volume; and under the arbitrage hypothesis mean reversion would be higher during periods of increased trading volume.

Trading volume in the futures market was used because it was assessed that the futures market was a more literal proxy for changes in hedging and speculative activity. In order to calculate a measure of relative increase or decrease in trading volume an expectations model was constructed as follows:

Let expected trading volume \( E(TVF_t) \) in the SPI futures market at time \( t \) equal:

\[
E(TVF_t) = \left( \frac{\sum_{j=1}^{30} TVF_{t-j}}{30} \right)
\]

(9.18)

where \( TVF_{t-j} \) is the trading volume at the same time on prior days. This means that the expected trading volume at any time of the day \( t \) will be the rolling average of the previous 30 day's trading volume which occurred at that particular time of the day. Deviations in expected futures trading volume at time \( t \) are then measured as follows:

\[
D(TVF_t) = TVF_t - E(TVF_t)
\]

(9.19)

A positive value signifies unexpected increases in trading volume and a negative value unexpected decreases. The time frame of this trading volume expectations model is short enough to take into account any contract expiration effects in trading volume, but long enough to smooth out any short term trading aberrations. The following model was then applied to test for mean reversion in periods of unexpected increases or decreases in trading volume:
\[ \Delta M_t = \sum_{v=1}^{2} \phi_v D_v M_{t-1} + \sum_{j=1}^{p} \lambda_j \Delta M_{t-j} + \nu_t \]  

(9.20)

where \( D_v \) is a dummy variable equal to one or zero when unexpected increases or decreases in futures trading volume are defined as:

\[
\begin{align*}
\nu = 1 & \quad \text{for an unexpected increase in trading volume} \\
\nu = 2 & \quad \text{for an unexpected decrease in trading volume}
\end{align*}
\]

The results are reported in Table 9.7. An increase in futures trading volume over and above the expected trading volume is associated with a higher mean reversion parameter and the F statistic shows that the mean reversion parameters are significantly different from each other at the 1% level. This result lends support to the hypothesis that unexpected increases in futures trading volume are not overwhelmingly associated with speculative activity. The results suggest that, on average, marginal increases in trading volume have a higher proportion of hedge transactions than normal trading volume.

**Table 9.7**

**MEAN REVERSION IN SPI INDEX FUTURES MISPRICING - UNEXPECTED TRADING VOLUME**

<table>
<thead>
<tr>
<th>Unexpected Trading Volume</th>
<th>Mean Reversion Parameter (( \phi_v ))</th>
<th>Standard Error</th>
<th>( \tau_u ) Statistic</th>
<th>F Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase</td>
<td>0.0387</td>
<td>0.00465</td>
<td>8.33***</td>
<td>19.89***</td>
</tr>
<tr>
<td>Decrease</td>
<td>0.0138</td>
<td>0.00489</td>
<td>2.81*</td>
<td></td>
</tr>
</tbody>
</table>

R-squared 0.1202 Durbin-Watson 2.004

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

\( H_{1v} : \ \phi_v = 0 \) against the alternative that \( \phi_v \) is greater than zero; \( \nu = 1, 2; \) tested using the Fuller (1976) \( \tau_u \) statistic.

\( H_{2v} : \ \phi_1 = \phi_2 \) against the alternative they are different.

### 9.4.8 Mean Reversion in Bull and Bear Markets

The information theories of Froot, Scharfstein and Stein (1992) and Campbell and Hentschel (1992) hypothesise that traders will tend to focus on one source of information
and that information arrival has an asymmetric effect on prices. For example, the arrival of sustained pieces of good news might induce traders to speculate on further price rises and to neglect arbitrage activities. Conversely, during a bear market traders might focus more on hedging activities rather than speculating on price falls.

These additional hypotheses were tested by splitting the data into bull and bear days. A bull day was defined when the value of the SPI futures index at 1600 was greater than what it was at 1000 - ten minutes after the opening of trading on that morning. A bear day was defined when the SPI price at 1600 was smaller than the 1000 price. By deleting the 0950 observation the impact of overnight information is controlled and the 'mood' over the remainder of the trading day captured. The applied model was:

$$\Delta M_t = \sum_{b=1}^{2} \phi_b D_b M_{t-1} + \sum_{j=1}^{p} \lambda_j \Delta M_{t-j} + \nu_t$$  \hspace{1cm} (9.21)

where $D_b$ is a dummy variable equal to one or zero where bull and bear days are defined as follows:

- $b = 1$ for a bull day
- $b = 2$ for a bear day

### Table 9.8

**MEAN REVERSION IN SPI INDEX FUTURES MISPRICING - BULL COMPARED TO BEAR DAYS**

<table>
<thead>
<tr>
<th>Type of Market</th>
<th>Mean Reversion Parameter ($\phi_b$)</th>
<th>Standard Error</th>
<th>$\tau_b$ Statistic</th>
<th>F Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bull</td>
<td>0.0256</td>
<td>0.00529</td>
<td>4.83***</td>
<td>0.57</td>
</tr>
<tr>
<td>Bear</td>
<td>0.0293</td>
<td>0.00527</td>
<td>5.54***</td>
<td></td>
</tr>
</tbody>
</table>

R-squared = 0.1168, Durbin-Watson = 2.004

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

$H_{1b}: \phi_b = 0$ against the alternative that $\phi_b$ is greater than zero where $b = 1, 2$; tested using the Fuller (1976) $\tau_b$ statistic.

$H_{2b}: \phi_1 = \phi_2$ against the alternative they are different.

The mean reversion parameter is higher on bear days compared to bull days ($\phi_1 > \phi_2$), and indicates that market participants may be, on average, slightly more 'speculative' on
bull days and arbitrageurs more active on bear days. However, as indicated by the F statistic the difference is not statistically significant. From these results it appears that there is only weak evidence to support the contention that as the mood of the market changes then the mean reversion parameter changes.

9.5 CONCLUSIONS

This chapter summarises the importance of mean reversion as a general concept in security markets. The possibility of futures-cash arbitrage provides a natural economic link between the two markets and a theoretical mispricing of zero. Arbitrage based arguments predict that changes in mispricing (or the basis) should be random and any deviations from fundamental value should be quickly arbitraged away. Miller, Muthuswamy and Whaley (1994) propose that observed mean reversion in futures mispricing (or the basis) is a statistical illusion caused by infrequent trading in the underlying stock index.

The Australian market provides a further opportunity to test for mean reversion because of the thinness of the stock market and a high level of infrequent trading. A summary of the results is as follows.

(i) There is mean reversion in the overall mispricing series which is robust across all futures contracts.

(ii) There is no distinct pattern in mean reversion as a function of time to maturity, which suggests that in Australia, arbitrage activity is not a function of contract maturity. This may be related to the fact that dividends in Australia are highly predictable and paid at set times of the year.

(iii) The strength of the mean reversion parameter is related to the level of mispricing in the previous period and is strongest outside the transaction cost bounds of 0.75%. Further, in Australia the mean reversion parameter is not significant inside the 0.75%
transaction cost window with the results more closely aligned to the UK results. Taken together these results support the hypothesis that mean reversion is arbitrage induced.

(iv) Mean reversion is lowest on Mondays, which has the lowest trading volume and highest on Tuesdays.

(v) During the trading day mean reversion is highest in the first hour of morning trading and the first hour after the lunch break. These results suggest that mean reversion is a countervailing factor to the over-reaction and negative price spikes in the individual markets, and that it is related to morning trading volume.

(vi) An increase in futures trading volume over and above expected volume is associated with a higher mean reversion parameter compared to reductions in expected trading volume. This supports the contention that increases in future trading volume are not overwhelmingly associated with speculative activity.

(vii) There is weak evidence to suggest that mean reversion during bear days is higher than on bull days. It may be that the 'mood' of the market is more optimistic during bull days, whilst there is more focus on arbitrage or hedging during bear days.

Overall, the results suggest that mean reversion exists in the Australian market, and that it is not dissimilar to the US and the UK markets, even though there is a stronger nontrading effect in the Australian market. Further, the tests indicate that increased trading volume is associated with stronger mean reversion which lends support to an arbitrage induced explanation. However, it should also be noted that the mean reversion parameters are still relatively smaller than what would be predicted in a market dominated by arbitrageurs.
10.1 BACKGROUND SUMMARY

10.1.1 Motivation and Contributions

The research in this thesis was motivated by the spectacular growth in the different kinds of financial derivative securities traded on the SFE, the recent microstructure research, the international linkages across markets, the impact of information on prices and the growing anomalies literature. The primary objective of the research was to develop a detailed and comprehensive empirical understanding of the micro impact of information flows on security returns, volatility, trading volume and arbitrage pricing across stocks in the AOI cash and SPI futures contracts. A secondary objective was to extend the relatively little research undertaken on the micro evolution of prices in futures markets in Australia.

The analysis of the impact of information encompassed both exogenous international impacts and spillover or feedback effects across related stock and futures markets. Whilst the primary focus was on analysing the transfer effects of information, it was also borne in mind that the initial information analysis may be contaminated by the underlying microstructures of the different markets and secondary information feedback across cash and futures markets.
The thesis makes several important contributions to the empirical literature in the area of information transfer and market microstructure. One of the more important contributions was the application of transfer function time series techniques to estimate how information was transferred. This is one of the few studies to date which have applied this methodology to this research problem. A second contribution was to compare the results across the AOI stock and SPI futures market and, therefore, examined impacts in markets with different trading microstructures.

A further research innovation undertaken in chapter five was to determine an intraday futures trading volume expectations model. Time varying polynomial functions were estimated across morning and afternoon trading sessions and the expected mood of the market. From these models a measure of the surprise in intraday trading volume was calculated and applied to intraday trading volume data.

The research into SPI arbitrage was extended by undertaking an intraday analysis of the arbitrage mispricing series and the impact of overnight information on that series. The role of arbitrage in the mispricing series was also explored by examining the mean reversion parameter as a function of a number of different factors. Finally, the extension of the research into the smaller thinly traded Australian market provided the opportunity to compare the empirical results with the previous research derived from larger more liquid markets.

In very general terms this thesis has found that a lack of trading liquidity in markets, the trading microstructure, and the exposure of markets to particular information arrival influenced intraday trading and price patterns. These are important considerations to be borne in mind by policy makers, regulators and market traders.

10.1.2 Background

The motivation and background for this thesis was outlined in the first three chapters. Chapter one provided the motivation and an economic background to the growth in
financial derivative markets over the last decade. The expected flow of information and
the structure of the Australian stock and futures market was outlined in chapter two. An
important feature of Australian security markets is that they open for trading after the
close of trading in the United States and there is overnight trading on the futures market
(SYCOM). It was also established that they have a number of unique trading procedures
and a study of the impact of public overnight information on opening prices was
particularly suited to the dependent thinly traded Australian market. The futures market,
because it has a different trading structure and trading clientele, provided an alternate to
the stock market to evaluate the impact of the same information set.

A range of information theories which sought to explain observed intraday price and
trading volume patterns and the processes whereby information is transferred into prices
were also reviewed. In a microstructure setting, the rational information models of
Admati and Pfleiderer (1988), Foster and Viswanathan (1990) and others, hypothesised
that price activity and trading volume would cluster around the release of private
information through trading. Other noise trading information models predicted that
prices would overreact to current information and mean-revert back to a fundamental
value after a price jump [DeBondt and Thaler (1989)], or there is price herding in the
short term [Froot, Scharfstein and Stein (1992)]. In summary, the explanations ranged
from a cognitive psychology view which suggested that investors tended to overweight
the value of current information, to the existence of noise traders who traded on the same
information and induced information spillovers and self-fulfilling expectations, through
to the contention that information is impounded into prices in a rapid and unbiased
manner.

Chapter two further reviewed a number of microstructure factors which could potentially
have an impact on intraday price and volume patterns. They included: (i) opening price
setting mechanisms such as call auctions; (ii) trading procedures such as open outcry
versus electronic trading; (iii) quote driven versus order driven price setting; (iv)
nonsynchronous trading in thin stocks on intraday indices; (v) speculative activity which
is attracted to specific markets; (vi) different trading times, lunchtime closure and the availability of after hours trading; (vii) the possibility that futures markets are more efficient in gathering macro information because of higher liquidity and lower transaction costs; and (viii) the possibility of information feedback through computer linked arbitrage trading.

Chapter three provided a literature review of the background empirical research in the stock and futures markets and the impact of feedback between the two markets. The chapter broadly established the existence of micro patterns in returns, volatility and trading volume and differences in the evolution of prices between cash and futures markets.

10.2 RETURNS, INFORMATION TRANSFER AND TRADING VOLUME

10.2.1 Returns and Information Transfer

Chapter four analysed intraday returns in the AOI and SPI. Unadjusted returns displayed a general U-shaped pattern with large positive spikes at opening and closing with negative reversals at 1015 hours and mid-afternoon. A time series transfer function model was then applied to the AOI and SPI returns in order to determine: (i) the functional form of the impact of overnight information and trading structures on the return series; and (ii) whether information and/or microstructural features are related to the intraday return spikes.

Overnight information was proxied by the previous day's return on the DJ65 Composite Index. Three theoretical models of possible information transfer - immediate impounding, diffused transfer and overreaction - were mathematically defined and tested. Autoregressive parameters incorporated into the model to account for thin trading in the AOI and bid-ask bounce in the SPI, and time of the day dummies were used to capture any specific time of the day effects which occurred at opening, closing or other times of the day.
After filtering out these effects, it was determined that approximately 37% of the opening price spike in the AOI was explained by these factors. The possibility that the remaining opening spike was related to some other public or private information set was then investigated. This was done by using the SPI futures as a secondary source to observe the effects of the impact of overnight information. First, it was found that the overnight DJ65 return had a higher impact on opening futures prices compared to opening stock prices. Second, there was a differential impact between the markets. The opening spike in the futures at 0950 was related solely to the external US market, but a large remaining 1000 spike (0.000426) was not related to overnight information. It appeared that the futures market first reacted to the overnight US information and then awaited developments in the Australian stock market, before then reacting to that market. This explanation, however, is at odds with a number of previous studies which argued that futures markets were less costly and more liquid to utilise than stock markets and, therefore, futures markets were likely to be more dominant in revealing macro information [Stoll and Whaley (1990a), Chan, Chan and Karolyi (1991) and others].

The fact that the futures market had a greater price change reaction to overnight information at 0950 and 1000 hours, suggested that the price setting mechanism of computer screen trading in stocks, compared to the open outcry system of futures, may be an effective mechanism in inhibiting price overreaction in the stock market. This hypothesis was examined by looking at the transfer effects of overnight information at 1015 hours. If the opening trading mechanism in the stock market was effective in restricting overreaction then there should have been no subsequent price reversal at 1015 hours, or at least, a restrained transfer of information into neighbourly prices should have occurred. The statistical evidence did not support this contention, with the impact of US returns being transferred into 1015 stock prices in a manner consistent with short term overreaction. The transfer function indicated that 13.7% of the initial price impact into the AOI from the US return was reversed at 1015. However, the reversal of the impact from the overnight information did not fully explain the negative spike at 1015 and it still remained. After filtering out the overnight effects, the 1000 (0.000263) and 1015
(-0.000269) returns in the stock market were approximately equal but opposite in sign. For the SPI futures market, there was no statistical evidence of any transfer into 1000 returns from the US market. The futures market waited a further fifteen minutes and the overreaction change occurred contemporaneously with the stock market at 1015. Similar to the AOI, about 12.5% of the initial impact from the US was reversed at 1015 with a remaining negative return spike of -0.000282. These observations supported a short term overreaction hypothesis in both markets [DeBondt and Thaler (1989)] and the results in the futures market suggested that traders may have short term horizons and tend to focus on one information source at a time [Froot, Scharfstein and Stein (1992)]. In summary, price overreaction was determined in two ways. The transfer function identified overreaction to the overnight information set and the time of the day dummies identified significant positive return spikes at 1000 and negative spikes at 1015 after the filtering process of the transfer function time series models was applied. The conclusion was an inherent overreaction at the opening of trading in Australia which was not explained by information arrival or trading microstructures.

Some other features which documented differences in the return structure between the two markets were also noted. The autoregressive process was strongly positive for the AOI series and weakly negative for the SPI series. This confirmed the prior perception that the Australian stock market suffered from a thin trading effect and the futures from bid-ask bounce. There was no evidence of any price transfer into subsequent prices, at or around the negative fixed time of the day effects at 1015 and 1430, in the SPI futures. In contrast, the significant coefficients on the evolution functions at these times for the AOI stock market suggested a slower mean reversion factor compared to futures prices. Finally, the closing price spike in the AOI was positive and significant, but this was not the case for the SPI.
10.2.2 Trading Volume

Chapter five documented the intraday trading volume pattern in the SPI futures market and tested for any incremental association with SPI and AOI price returns over and above the explanatory power of the time series transfer function models developed in chapter four. A U-shaped pattern in intraday futures trading volume was observed with the intensity of trading the highest during the last ten minutes of trading. Average daily trading volumes were highest on bull days and lowest on Mondays. The lower trading volume on Mondays was a consequence of much lower trading in the morning directly after the weekend nontrading period.

Intraday polynomial functions were fitted to the trading volumes for Mondays and bull and bear days. It was found that a quadratic function best described trading volume in the morning with a cubic function in the afternoon. The functional form also differed between Mondays and bull and bear days.

Consistent with the research of Bessembinder and Seguin (1992, 1993) it was found that unexpected trading volume had a stronger association with returns compared to raw trading volume. The log of raw trading volume was not significantly related to AOI or SPI returns. Further, the log of the difference between the polynomial models (as measures of expected trading volume) and actual trading volume had greater explanatory power compared to a random walk model. Furthermore, contemporaneous surprises in trading volume were found to be negatively related to returns and surprises in trading volume lagged one period had a positive relationship with returns. The above results may be construed as support for hypotheses which predict that futures trading volume leads price changes, rather than trading volume lagging price changes. The empirical results also supported prior observations that there is less evidence that trading in derivative markets has a contemporaneous positive correlation with price changes [Bessembinder and Seguin (1992), Locke and Sayers (1993)] when compared to stock markets [Jain and Joh (1988)].
10.3 VOLATILITY

The volatility of stock and futures markets has long been a concern of regulators, policy makers, market traders and the public at large. Chapters six and seven examined several aspects of volatility.

10.3.1 Short Term Volatility

In chapter six the interday variance ratio methodology of Amihud and Mendelson (1987) was used to examine the impact of the lagged opening price setting mechanism in the Australian stock market on opening prices. The open to close variance ratio in the futures market was 1.067 and in the stock market it was 1.018. This initial result suggested that opening the market with a continuous open outcry mechanism (as was the case in futures) would increase the relative volatility of prices. However, the 1015-to-close variance ratio in the AOI was 1.185 which was a similar magnitude to the open-to-close variance ratios observed in the US and Japan. This suggested that the opening price setting mechanism for stocks in Australia did not mitigate volatility but only served to postpone volatility until the following period. The results also supported the conclusions that opening price setting mechanisms impact on opening volatility and that the open outcry system utilised in the futures market did not induce excessive relative volatility.

The trading and nontrading approach of French and Roll (1986) was also applied to the data and it was found that there was significantly greater intensity of volatility during trading hours compared to nontrading hours. Further, the ratio of trading to nontrading volatility in futures was some 26% higher than the stock market and the trading time volatility was higher and more persistent in the futures market. It was also observed that the resumption of futures trading after lunch was associated with an increase in volatility in both markets of about 10%. Further, resumptions of trading after overnight and lunchtime trading halts in Australia were associated with higher volatility.
The study of volatility was then extended to an intraday analysis using 15-minute observations. An L-shaped pattern in intraday volatility\(^1\) was found with the opening volatility in both markets up to ten times greater than the interior volatilities. The closing volatilities showed a small spike but it was not of the same magnitude observed in the US. The much smaller closing volatilities in Australia may be associated with different trading procedures. The SPI was computer traded from 1645 hours to 0400 hours (SYCOM) and potentially reduced the overnight risk for traders who could enter and exit the market as overnight information emerged. This factor could have reduced the closing volatility which might have been otherwise induced by risk averse traders exiting the market.

Another potential explanation is related to the Admati and Pfleiderer (1988) model which hypothesises that the act of opening and closing a market forces an increase in non-discretionary liquidity trading which, in turn, attracts private information and discretionary liquidity traders. The fact that intraday futures trading volume in Australia is highest at the end of the day but is not associated with an upturn in volatility is unexplained and contrasts with the predictions of Admati and Pfleiderer (1988). This unexplained effect could be due to a limited supply of private information traders in Australia. In combination with the dependence of Australia on overnight information, limited private information traders may have chosen to cluster at the opening of the market along with public information traders. The increased trading volume at the end of the day may then only be related to a higher proportion of non-discretionary liquidity traders or noise traders and because their trading activity has no information content then price volatility might remain unchanged. This hypothesis could be tested by further research.

Chapter six also reported that the intraday volatility in the SPI futures market was consistently 70-80% higher than the AOI stock market. One potential explanation was

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\(^1\) This pattern was robust across a number of volatility proxies including variance and standard deviation of returns, absolute returns and squared returns.
that the thin trading in the Australian stock market dampened the observed intraday AOI volatility. This factor was accounted for by comparing the futures volatility to the relatively more liquid TLI index and by making an adjustment directly to the AOI. Depending on the adjustment, the thin trading feature explained between 23% to 49% of the difference in volatility. The remaining higher volatility in the SPI was hypothesised to be related to information effects or to speculative activity.

The relative impact of private and public information as a cause of the high opening and persistent volatility was then examined. The impulse function fitted to the previous nights closing volatility (as a proxy for private information) had very little explanatory power for the opening AOI volatilities. For the SPI the relationship was negative and indicated that the closing volatility in the futures market did not predict subsequent volatility or represent private information. On the other hand, overnight public information modelled as an intervention and transfer function on the previous days DJ65 volatility had significant explanatory power for the opening volatilities. Public information had a relatively larger impact on the futures market opening volatility and explained more of the opening volatility spikes. The autoregressive time series model fitted to the volatilities revealed that the futures market had a longer and more persistent volatility memory which lasted almost two days. These results led to the conclusion that the excess short term volatility of futures markets may be more related to noise trading rather than information effects.

10.3.2 Long Term AOI Volatility

The question of whether the higher unexplained short term volatility in the futures market was transferred across into the underlying stock market was answered in chapter seven. Using an a priori argument it was determined that the economic and social costs of short term and infrequent periods of excess or undesirable volatility were minimal when compared to sustained long term effects. A key research issue was determined as
whether futures and derivative futures trading caused any long run increase in stock market volatility.

The introduction of the SPI futures index in February 1983 and the SPI futures options in June 1985, together with the availability of relevant data relating to the AOI, enabled a number of statistical tests to be undertaken on the long run stock market volatility in Australia. Using time series techniques, the results indicated that the introduction of trading in the SPI futures and futures options markets did not affect the long term volatility of the AOI, measured on either a daily or weekly basis.

It was noted there difficulties in designing tests to settle this research question. Along with previous research the analysis in chapter seven was a joint test of no change in volatility and no intervening effects and there were possible problems with confounding or intervening variables. For example, the floating of the Australian dollar in late 1983, the continued deregulation of stock exchanges, and the changing of foreign bank ownership and mutual fund investment rules. However, it was also noted that the analysis of the AOI data reinforced the majority of the previous US studies that concluded that futures market trading had no effect on the underlying long run volatility in the cash markets. Based on this evidence it appeared that the unique nature of information dependence and the different trading features of the Australian market, combined with the introduction of futures trading, did not adversely affect the long term volatility in the stock market. Any spillover effects (if any) from the SPI to the AOI are likely to be short term in nature and the lead-lag nature of volatility spillover in thinly traded markets is an obvious area of further research.

10.4 ARBITRAGE AND MEAN REVERSION

It is well known that the availability of an underlying basket of stocks and a futures contract written on those stocks provides an arbitrage link between cash and futures markets. The effectiveness of the link is dictated by a number of factors including the
efficiency of markets, the expectations of participants, transaction costs, the flow of information between markets, differential trading structures and the availability of arbitrage capital. Chapters eight and nine analysed the intraday arbitrage relationship between the SPI and the AOI and the mean reversion in the mispricing series. These chapters are distinguished in that they are one of the few studies which have analysed the behaviour of the stock index futures arbitrage series on an micro basis in Australia.

10.4.1 Arbitrage

Chapter eight noted that some considerable research has focussed on stock index arbitrage strategies and the documentation of deviations from 'fair values'. In an efficient market there should be no evidence of sustained arbitrage mispricing or any structural dependence in the mispricing series - the path of the series should fluctuate randomly around zero. It was noted that overseas researchers have consistently documented substantial and predictable arbitrage mispricing between the stock index and index futures contracts.

The chapter outlined the arbitrage principle and applied that principle to establish a fair value for a stock index futures contract. The mispricing series for the stock price index contract was then calculated using the actual traded price and the theoretical futures price. Consistent with previous overseas studies, the mispricing series did not fluctuate randomly around zero. The series had a high positive autocorrelation coefficient at the first lag and was positive and significant up to at least four lags, with the series consistently remaining above and below zero for prolonged periods. These results were found to be robust across the four contracts examined. Further, the mispricing series did not show any significant difference across days of the week except for a tendency for the positive mispricing to decay from the late morning period on Fridays. Mispricing at the close of trading showed a sharp decline and was significantly different from mispricing at other times during the day. However, the overreaction and unusual behaviour at the opening of the AOI and SPI markets identified in chapter four did not translate into any significant mispricing spikes at opening. These results reinforce the perception that
something unusual happens at the start and end of the trading day. Trading halts are highly influential. This is even the case in Australia where the risks associated with market closure were significantly reduced because of the availability of after hours trading.

The impact of overnight information on the opening mispricing series was then examined by applying the time series transfer function model described in chapter four. It was found that the previous day's return on the DJ65 had a positive impact on the mispricing series at the opening of trading of the Australian market. That is positive returns on the previous day's DJ65 increased the mispricing spread and negative returns reduced the spread. Moreover, this impact was transferred across into three subsequent 15-minute periods. The contention that this effect was driven by the thin trading problem in the stocks which constituted the AOI was examined by splitting the mispricing series into bull and bear days. It was found that intraday mispricing was positive and declined over the course of bear days and that the mispricing series increased during trading on bull days. This effect was opposite to that predicted by the nonsynchronous trading hypothesis.

### 10.4.2 Mean Reversion

Chapter nine summarised the importance of mean reversion as a general concept in security markets. The possibility of futures-cash arbitrage provided a natural economic link between the two markets and, in an efficiently priced market, a theoretical mispricing of zero. Arbitrage based arguments predicted that changes in mispricing (or the basis) should be random and any deviations from fundamental value should be quickly arbitrated away. Miller, Muthuswamy and Whaley (1994) proposed that any observed mean reversion in futures mispricing was a statistical illusion caused by infrequent trading in the underlying stock index. The Australian market provided a further opportunity to test for mean reversion in a market characterised by a high level of infrequent trading.
It was found that there was mean reversion in the overall mispricing series which was robust across all futures contracts studied. Mean reversion was lowest on Mondays and highest in the first hour of morning trading and the first hour after the lunch break. These results indicated that mean reversion may be a counterveiling factor to the overreaction and negative price spikes in the individual markets, and that it may be related to trading volume.

An increase in futures trading volume over and above expected volume was associated with a higher mean reversion parameter compared to reductions in expected trading volume. This supported the contention that increases in future trading volume are not overwhelmingly associated with speculative activity and encompassed a component of arbitrage trading.

There was also some weak evidence of a psychological component in arbitrage trading. Mean reversion during bear days was found to be higher when compared to bull days. It may be that the 'mood' of the market was more optimistic during bear days, and there was probably more of a focus on arbitrage or hedging during bear days. Finally, the strength of the mean reversion parameter was related to the level of mispricing in the previous period. It was strongest outside the transaction cost bounds of 0.75%, and not statistically significant inside the 0.75% transaction cost window.

Taken together the overall results suggested that mean reversion existed in the Australian market and that it was not dissimilar to the US and the UK markets, even though there was a stronger nontrading effect in the Australian market. It was noted that the mean reversion parameters were still relatively smaller than what would be expected in a market dominated by arbitrageurs. The more important result was that arbitrage was only significant at much wider transaction bounds when compared to the US. This signified an absence of low cost arbitrage traders in Australia and adds to the previous contentions that there may be limited information traders operating in Australian markets.
10.5 FURTHER RESEARCH

An obvious extension for this thesis is to extend the studies undertaken by employing a much broader data set. The Australian data set could be extended by collecting data over a number of years. Further, the extension to Asian markets which have different trading structures and (possibly) trading psychology to Australia, but which also rely on overnight information from the US and Europe, offers a number of interesting research possibilities about information transfer into intraday prices and trading volume.

The application of transfer functions to estimate the form of financial time series or the functional process whereby information is diffused into prices provides extensive research opportunities; for example, the application of transfer function models to describe and predict financial time series with large and dynamic price spikes, or the evolution of prices after trading halts, or to determine the impact of information releases on financial market prices. Such information events could include the release of Balance of Payment figures, other macroeconomic releases, the impact of changes in interest rates on exchange rates, or the closure of stock markets by authorities when sensitive information is released.

There are a number of potential applications in accounting capital market research or management accounting. Information transfer from the release of earnings reports and the transfer effect across prices of non-release firms in the same industry, could be modelled using transfer function techniques. The impact of downtime in factories and the ripple affect across cost structures is another application.

With regard to research on trading volume the results for the US generally show a contemporaneous relationship between trading volume and returns [Jain and Joh (1988), Bessembinder and Seguin (1992, 1993)] but use raw trading volume as a measure of information. There are two obvious and important aspects for future research using intraday data. First, surprises in trading volume are more likely to convey greater incremental information and this area should be a fruitful area of research in the near future. Secondly, the expectations model of intraday trading volume should take into
account the different trading patterns observed for various markets over intraday times and days of the week.

It may well be that trading volume in thinly traded markets means that surprises in trading volume have a greater speculative impact on prices because of the smaller trading base. This may not be the case in larger well traded markets where the MDH hypothesis (which predicts a contemporaneous relationship), or the SIC hypothesis (which predicts that trading volume will lag price changes) might hold for surprises in intraday trading volume. These are areas for further research, and the price-volume relationship in financial markets offers the promise of a number of fruitful research opportunities.

Further research could centre around an examination of whether prices in financial markets have mean reversion properties. This research problem would be particularly interesting after shocks to the price series and should examine whether some financial markets display a stronger or weaker mean reversion than others. This type of research would throw light on the relative efficiency of the arbitrage process within those markets or examine the markets ability to rebound from shocks. The application of mean reversion processes could also be applied to time series other than stock and futures markets. For example, the time series behaviour of accounting variables such as earnings or earnings ratios would be an interesting application.

Finally, the simultaneous estimation of transfer function models along with general autoregressive conditional heteroscedastic (GARCH) and related models would be an interesting technical challenge.
REFERENCES


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