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Abstract

This paper examines the impact of automated trading in the stock market on the information transmission between the stock and futures markets. This issue is of particular relevance given the trend of exchanges to introduce automated trading. We focus on the Australian market as its institutional features and recent changes in trading systems have created an ideal environment for examining this issue. We initially find evidence of a substantial bidirectional information flow between the stock and futures markets. The paper then focuses on the period surrounding the move by the Australian stock exchange to automated trading. After the introduction of automated trading, we find a significant change in the information transfer process between the two markets. The findings are consistent with the hypothesis that automated trading results in a richer and more timely information set which accelerates the price discovery process. However, the evidence is not overwhelming and alternative explanations exist.

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1. INTRODUCTION

A recent announcement by the Sydney Futures Exchange[1] (SFE) to fully automate futures trading is a specific example that highlights the trend by securities exchanges to move away from a trading floor structure towards screen trading.[2] Yet there still exists a diversity of market structures used to trade both equities and futures throughout different countries which implies that the superiority of one market structure over another is questionable.[3] Furthermore, empirical evidence on the benefits of automated versus floor traded markets is limited.[4] This paper extends previous research by examining the impact of financial market automation on information flow and price discovery.

It is argued by Grunbichler, Longstaff and Schwartz (1994) that automated markets offer more efficient price discovery due to the lower costs of trading, faster trade execution, cleaner information capture and dissemination, and greater transparency with respect to prices and quotes. They document that returns on the screen traded German DAX index futures contract exhibit a greater lead time over returns on the floor traded DAX equities index and less feedback than has been documented for floor traded futures and floor traded equities in the USA.[5] The authors directly attribute this result to the increased price discovery attributes as a result of the automation of the futures market. The main purpose of this paper is to re-examine Grunbichler, Longstaff and Schwartz's (1994) hypothesis by using the unique market structure of the Australian futures and equities markets in order to bring further evidence to bear on the issue of automation and information flow. In Australia, index futures are floor traded and equities are screen traded. Hence, the market structures used to trade futures and equities in Australia are the reverse of those used in Germany. Further, the Australian stock exchange has effectively changed equity trading from a floor based to a screen based system.

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[1] See *Australian Financial Review*, 24 October 1997.

[2] Other examples include the automation of the London Stock Exchange in 1986, Tokyo Grain Exchange in 1988, Stock Exchange of Singapore in 1988 and the Jakarta Stock Exchange in 1995. While the preceeding exchanges changed from floor trading to automated trading, exchanges such as Germany's Deutshe Terminborse and MEFF Renta Fija (the Spanish Financial Futures and Options Exchange) were created in 1990 as automated exchanges. See *Euromoney*, July 1998, pp.33-37 for a review.

[3] Examples of automated stock (futures) markets are the London Stock Exchange (Deutsche Terminborse). Examples of floor traded stock (futures) markets are the New York Stock Exchange (Chicago Mecantile Exchange).

[4] Empirical investigations of the impact of financial market automation include Schmidt and Iversen (1993), Grunbichler, Longstaff and Schwartz (1994), Shyy and Lee (1995), Pirrong (1996) and Franses, Van Ieperen, Martens, Menkveld and Kofman (1997) and Kofman and Moser (1997).

[5] Grunbichler et al (1994) compare their German results to those of Stoll and Whaley (1990) who examine the S&P 500 index futures contract and stock index.

A reexamination of the Grunbichler, Longstaff and Schwartz (1994) hypothesis is warranted due to the fact that their conclusions are dependent on an international cross-market comparison. The longer lead time documented for German markets in their paper may well be driven by differences in reporting lags (Stoll and Whaley 1990), transaction costs (Harris 1990, Flemming, Ostdiek and Whaley 1996) and liquidity (Grunbichler, Longstaff and Schwartz 1994) between German and US markets rather than the market structure *per se*. The procedures used to automate the Australian Stock Exchange between 1987 and 1990, facilitates the construction of a research design which avoids these problems and allows us to construct a direct test on the specific change from floor trading to screen trading. On 3 September 1990, ninety-five of the largest Australian stocks were transferred from floor trading on regional exchanges to screen trading on the Stock Exchange Automated Trading System (SEATS). The data set available for this study spans this date for both the Share Price Index futures contract and the All Ordinaries Index and, consequently, permits an examination of the lead-lag relationship before and after automation of the equities market. This type of analysis overcomes many of the problems inherent in research utilising cross-market comparisons and allows a direct test on the effects of automation.

This paper is organised as follows. The next section theoretically outlines the determinants of information transmission and presents our hypotheses. Section three provides a description of the automation process of the Australian stock market and institutional background. Section four describes the data set. Section five presents the results for the lead-lag information attributes between the stock and futures markets and analyses the impact of the automation of the stock market on that information transfer process. The paper is concluded in section six.

2. THEORETICAL CONSIDERATIONS

Grunbichler Longstaff and Schwartz (1994) identify four ways in which screen trading can effect price discovery which are relevant in the current context.[6] First, screen trading is more cost effective than floor trading. In a competitive market setting, these lower costs will be passed onto traders in the form of lower transaction costs.[7] Therefore, the expected profitability from an informed trade is greater and hence there follows an expectation of increased activity and concentration of informed trading around information. Second, orders can be processed, routed and executed more rapidly in an automated trading environment, thus enhancing the ability of traders to react to information in a timely manner. Third, information capture and dissemination is more rapid under automated trading, thus keeping traders informed on a more timely basis. Fourth, the greater volume and transparency with respect to trade and quote information offered by an electronic open limit order book can also enhance a trader's ability to assimilate and react quickly to information. In summary, these reasons support an expectation of a richer and more timely information set.

Further, Flemming, Ostdiek and Whaley (1996) demonstrated that the leveraged nature of derivative contracts imply that the costs of trading futures are a small fraction of the costs of trading a similar position in underlying equities.[8] Automating an equities market is unlikely to substantially change these relative costs. This implies that informed traders are likely to first trade in the futures market, regardless of whether the underlying spot market is automated. Hence, new information is expected to initially be reflected in the futures market both before and after automation of the spot market. Hence, in Australia the Share Price Index futures contract (SPI) is expected to generally lead the All Ordinaries Index (AOI) both before and after the introduction of SEATS.

Notwithstanding the above argument, the nature of a futures index contract implies that it is unlikely to be used as an instrument for exploiting firm-specific information. A futures index contract gives traders the opportunity to exploit macro-based information which is expected to move the market as a whole. Firm-specific information is only reflected in futures index prices through the component stocks. Thus, traders seeking to exploit firm-specific information will use the index component

[6] They also argue that the higher level of anonymity offered by screen traded environments may discourage informed traders. However, screen trading on the ASX offers a similar level of transparency to floor trading which took place prior to the introduction of SEATS.

[7] For example, exchange fees charged to brokers may decline which can lead to a decline in brokerage fees as these costs are ultimately passed on to the client.

stocks as their tradeable instrument. In these circumstances, firm-specific information will first reveal itself in stock prices and the underlying stock index before being transmitted to the futures market. Therefore, we expect to observe some evidence of the AOI leading the SPI both before and after the introduction of SEATS. That is, we expect a bidirectional lead-lag relationship between the two markets. Indeed, confirmatory evidence of such a relationship has been found in overseas markets (see Chan, Chan and Karolyi 1991, Subrahmanyam 1991, Chan 1992). Initially we seek to test the bidirectional relationship in the Australian markets.

The main and subsequent research question is how the information flow between the stock and futures market changes after automation of the stock market. We draw upon the arguments above which imply that an environment of richer and more timely information is created after automation. These changes lead to the following three hypotheses. First, the automation of the stock market will increase the contemporaneous information link between the two markets through an increase in the contemporaneous response coefficient. Second, given the SPI will lead the AOI irrespective of the trading mechanism, there will be stronger AOI response coefficients at close lags and weaker AOI response coefficients at longer lags after automation of the stock market. Third, firm-specific information will be incorporated in the stock market more quickly after automation and this will increase the rate of feedback from the stock market to the futures market. Hence, there will be stronger SPI response coefficients at close leads and lower SPI response coefficients at longer leads after automation. In essence, we picture a flatter information transfer curve before automation which is transformed into a more peaked curve with thinner tails after automation.

Note that our hypotheses concern the relative magnitude of lead-lag response coefficients and centre upon the speed of information transmission between the two markets. The hypotheses do not make any claims about the absolute volume of information or the mix between public and private information. These factors are problematic to control given our inability to observe private information although we provide some proxy evidence concerning this issue later in the paper.

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[8] In fact, they document that total costs associated with trading one S&P 500 index futures contract are one thirtieth the cost of trading an equivalent portfolio of equities.

3. INSTITUTIONAL BACKGROUND

Trading in the Share Price Index (SPI) futures contract on the Sydney Futures Exchange (SFE) began in 1983 and is conducted by open outcry on the trading floor of the exchange.[9] The SPI futures contract is based on the underlying All Ordinaries Index which is comprised of screen traded stocks and is calculated by the Australian Stock Exchange (ASX) every minute. To execute a trade in the SPI one or more traders must vocally accept a bid or offer from another trader.[10] While *price* priority is enforced on the floor, trading does not occur according to formal *time* priority rules. All bid prices, ask prices, trade prices and trade volumes are recorded by an exchange official in the pit who relays the information via microphone to data entry clerks on a catwalk above the exchange floor. This information is entered into computer terminals which are linked to information boards around the walls of the trading floor and is also electronically transmitted in real time to information vendors. The information boards report cumulative trade volume, the last four trade prices, the best bid and best ask prices and the high and low of the day. On-market crossing of offsetting orders held by a single broker are permitted in the SPI pit however, each side of the trade must be bid or offered to the whole market prior to execution. There is no off- market trading allowed by the exchange except when Exchange for Physical (EFP) transactions are negotiated off the floor.[11]

Trading in the component stocks of the All Ordinaries Index prior to 1987 was by open outcry on the trading floors of the six regional stock exchanges located in Sydney, Melbourne, Brisbane, Perth, Adelaide and Hobart. Brokers and exchange members were permitted to trade for clients or their house account respectively. Traders called out bid and ask prices for stocks which were recorded by 'chalkies' on information boards on the walls of each exchange along with a broker identification code.[12] The information boards displayed the current best bid and ask quotes available. These quotes were indicative only but gave the bidder or offeror a few moments of time precedence to participate in any trade on that stock. Best bid, best ask, high, low and last trade

[9] Open outcry trading on the Sydney Futures Exchange is similar to that used on the Chicago Mercantile Exchange.

[10] Traders in the SPI pit include brokers who execute business for clients, locals who trade for their own account and principal traders who trade for their house account. Principal traders, while permitted to trade on the floor, are few in number. It is estimated that locals account for approximately 30% of the volume in the SPI pit with brokers accounting for the rest.

[11] EFP transactions involve the simulatenous trading of a position in the underlying market and an offsetting futures position to gain an instantaneous hedge.

[12] The information boards were large chalk boards with the name of each stock listed on them. Chalkies recorded the best quotes on each issue as they were called onthe trading floor. The volumes associated with quotes were not specified or recorded.

prices on all stocks traded on the regional exchanges were also captured by price reporters in real-time and entered into a computer network that linked each of the regional trading floors. The system was responsible for both capturing and disseminating trade information to market participants across Australia. To effect a trade, a counterparty had to physically search out the quoting party and negotiate the price and volume of the trade which were then recorded on trading slips. These slips were the only record of trades and were given to data entry clerks on the floor of the exchange who then entered them into a central database. On-market crossings of trades were permitted once both sides of the trade had been bid and offered to the market. Off-market trading was also permitted for large parcels greater than $500,000 in value provided the details of the trade were reported to a crossings clerk on the floor of the exchange. Daily reports of off-market trades were made available to brokers and exchange members.

Between 1987 and 1990, trading in ASX listed stocks was automated. The process of automation involved 13 stages where groups of stocks were successively transferred onto SEATS.[13] SEATS is an electronic open limit order book comprising a network of computer terminals which allow brokers to submit orders.[14] To effect a trade, SEATS matches offsetting orders that are submitted based on price and then time priority rules. Trade and quote information is captured on-line in real-time and immediately routed to information vendors. SEATS operators are able to see all bid and ask orders including prices, volumes and broker identifiers. The only exception to this is undisclosed orders where volumes are not required to be revealed for orders of over $100,000.[15] On-market crossing of orders held by the same broker is permitted on SEATS.[16] Furthermore, off-market trading is also allowed under special circumstances and must be reported to the market immediately through SEATS.[17]

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[13] On 19 October 1987, an initial 21 stocks were transferred on to SEATS. Following this, 20 stocks were transferred on 27 January 1988, approximately 200 inactive industrials on 1 February 1988, 185 inactive industrials on 16 May 1988, 250 inactive industrials on 12 September 1988, the remainder of inactive industrial stocks on 19 September 1988, all second board stocks on 31 October 1988, M-Z mining stocks on 21 November 1988, F-L mining stocks on 5 December 1988, A-E mining stocks on 19 December 1988, 16 mining, 29 industrial and 19 suspended stocks on 10 July 1989, and alpha (largest 95) stocks on 3 September 1990. The alpha stocks could only trade parcels less than $25,000 on this date. On the 1 October 1990 trades of all sizes in alpha stocks were transferred to SEATS completing the automation of the exchange.

[14] See Glosten (1994) for a characterisation of an electronic open limit order book.

[15] From 1987 to 1992 the minimum size to enter an undisclosed order was $25,000.

[16] On-market crossings are able to circumvent time priority rules. While both sides of the order must adhere to normal price priority, each side of the order is given priority execution within a given price step.

The data used in this study cover the period April 1989 to February 1992. The period spans the last two stages of the automation process and includes the introduction of 99 of the largest (alpha) securities to SEATS on 3 September 1990. Ninety-five of these stocks were in the All Ordinaries Index at the time. From 3 September 1990, these stocks were permitted to be traded on both the regional exchange floors and on SEATS. By 1 October 1990, however, trading in all stocks was entirely screen based.[18] The 95 index stocks that were allowed to trade both on the floor and on SEATS represented 87.6% of the market capitalisation of the All Ordinaries Index.[19] However, many of these stocks had previously been transferred to SEATS and indeed trade records captured from SEATS indicate that 32 of these stocks had traded on SEATS prior to 3 September 1990. Analysis of trade records also confirm that the remaining 63 stocks, representing 61.8% of the index first traded on SEATS on 3 September 1990.

Automation of equities trading consequently had a three-fold effect on the market. First, the transparency of the market with respect to price and trade information was improved radically with participants able to view the entire bid/ask schedule and course of sales in real time. Second, reporting lags and errors were reduced due to instantaneous dissemination of all market activity via electronic signals thereby producing a cleaner price feed for the market. Third, faster trade execution was achieved for large portfolios of stocks as parties to transactions no longer had to physically search each other out.

FIGURE 1 ABOUT HERE

Figure 1 illustrates the attributes of the index stocks that traded on SEATS between April 1989 and February 1992. Prior to 3 September 1990, trades occurred on SEATS for approximately 150 stocks or 50% of total index stocks. This group however, represented only 30% of the total market capitalisation of the All Ordinaries Index. By 1 October 1990, approximately 270 index stocks

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[17] Off-market trading is permitted for crossings, specials (trades greater than $1 million in a single stock) and portfolio specials (trades of more than $2 million in at least 10 different stocks).

[18] The dual trading trial lasted only 3 days due to the high cost of running two systems simultaneously. During the period of the trial trades greater than $25,000 in alpha stocks could only be executed on the regional exchange floors and not on SEATS.

[19] The All Ordinaries Index is the primary equity index computed by the ASX. It is a broad-based value-weighted index incorporating approximately the largest 300 stocks.

actually traded on SEATS representing almost 100% of both the total number of index stocks and the total market capitalisation of the index.[20]

4. DATA

The SPI futures database was originally provided as pit traded transaction data time stamped to the nearest second. The SPI prices used relate only to the near dated futures contract,[21] which is rolled over to the next traded contract after expiration at midday on the last business day of March, June, September and December. Following Stoll and Whaley (1990), Chan (1992) and Grunbichler et al (1994), five-minute observations were derived from the transaction base by abstracting the nearest price traded directly after each five-minute period. For the AOI, which is computed as a capital gains index and reported every minute, a database of five-minute observations was obtained from ASX records.

As the Australian stock and futures markets do not trade over identical times, contemporaneous data were obtained by discarding observations from periods when only one market was open.[22] Observations for which there was zero SPI trading volume were also excluded.[23] Further, observations for the month of the main introduction of automation (September 1990) were deleted leaving a seventeen-month window either side of automation. The final sample consisted of 24,825 observations over the periods April 1989 to August 1990 and October 1990 to February 1992.

Price changes (returns) were estimated from the difference in log price relatives, viz:

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

[20] The total number of index stocks that traded on exchange floors (screen traded) was calculated for August 1989 and April 1990 using data extracted from the *Australian Financial Review*. 130 (165) and 132 (150) index stocks traded on the regional trading floors (SEATS) during the months of August 1989 and April 1990 respectively. These stocks represented an average of 44% (50%) of stocks in the All Ordinaries Index.

[21] The near-dated contract typically is the heaviest traded contract and therefore this contract is least likely to suffer from thin trading.

[22] SPI observations between 9.50 am and 10 am and between 4 pm and 4.10 pm, and AOI observations between 12.30 and 2 pm, were discarded.

[23] The removal of observations with zero trading volume was designed to eliminate stale prices. As a result about 7% of the original observations were removed which were evenly spread over the sample.

The descriptive statistics of the price changes for both the AOI and SPI are presented in Table 1 which shows that returns on the SPI have a lower mean and higher volatility as evidenced by the standard deviation and range, compared to returns on the AOI.

TABLE 1 ABOUT HERE

Table 2 reports the autocorrelation coefficient estimates for the two series. The AOI has a high and statistically significant positive first order autocorrelation in price changes. Significant coefficients are also observed out to four lags, consistent with previous research in Australia,[24] and theoretically consistent with the presence of thin trading in the component shares of the index.

In contrast, the SPI exhibits negative and smaller first order autocorrelation in price changes. This is consistent with bid-ask bounce in futures markets, the higher liquidity of futures markets, and compares with the first order intraday autocorrelations of -0.068 observed for the S&P 500 index, 0.042 for the Major Market Index futures (Chan 1992) and 0.034 for the DAX futures (Grunbichler et al 1994).

TABLE 2 ABOUT HERE

5. THE LEAD-LAG RELATION

5.1 Lead-Lag Attributes

In this section the focus is on the lead-lag relation between the AOI and SPI futures returns. Consistent with Stoll and Whaley (1990) and Grunbichler (1994), we utilise a multiple regression framework to identify the lag-lead relations. First, however, the effects of infrequent trading in the AOI and bid-ask bounce in the SPI are controlled by estimating an ARIMA model for each series. Identification of these models indicates that both time series are well described by an AR(4) process. In turn, the return innovations from the AR(4) processes are then used in the regression model. We denote the AOI return innovations as $\hat{R}_{AOI,t}$ and regress them on the lagged futures innovations $\hat{R}_{SPI,t}$ the contemporaneous futures innovations, and leading futures innovations using the following general model:[25]

[24] Brailsford and Hodgson (1997) observed a first order coefficient of 0.19 for a similar data set.

[25] A significant lagged futures coefficient denotes that the futures market leads the stock market and vice-versa.

$$\hat{R}_{AOI,t} = \alpha + \sum_{j=-J}^{+J} \beta_j \hat{R}_{SPI,t+j} + \varepsilon_t \qquad (2)$$

When $\hat{R}_{AOI,t}$ is the AOI innovation, $\hat{R}_{SPI,t}$ is the SPI innovation. In order to avoid comparing returns on different days, only futures returns for the same day were applied in the regression. Table 3 reports the results of the regression which is run for the full sample of 24,825 observations. We ran the regression in (2) using a variety of leads and lags (ie. varying J). For parsimony, we report only the first five leads and lags noting that the coefficient estimates beyond five leads and lags were all insignificant.

TABLE 3 ABOUT HERE

Consistent with the results of overseas studies, our results show a significant contemporaneous relation between stock and futures innovations. Compared to the German market (Grunbichler et al 1994) the contemporaneous relation is lower in Australia (0.099 versus 0.710). There is also evidence that the futures market leads the cash market by up to twenty minutes. The response coefficients for the leading futures returns are also large in economic terms, ranging from 0.0567 for the first lag to 0.0063 for the fifth lag.[26] Moreover, the F- statistics for the hypotheses that the first five lags are equal to and sum to zero are rejected, hence providing further evidence that the SPI leads the AOI.

However, there is also feedback between the stock and futures market with the stock market leading the futures market for up to ten minutes with a particularly high response coefficient at the first lead. The F-statistics for the joint significance of the first five leads support the observation of information feedback from the stock market to the futures market. One other feature is that, whilst the stock market gives a strong short term lead to the futures market, the futures market provides a lead to the stock market over a longer period.

In summary, these results are consistent with a bidirectional information flow between the stock and futures markets in Australia thereby confirming overseas findings. The distinguishing features are a

[26] These coefficient estimates are similar to those found in other markets.

significant contemporaneous relation, a strong five-minute feedback from the stock market to the futures market and a feedback from the futures market to the stock market of up to twenty minutes.

5.2 The Impact of Automation

Having established the overall lead-lag characteristics of the Australian market we now turn to an analysis of the impact of automation. Since the major impact of the automation in the stock market occurred in September 1990, we re-run the regression model using a dummy variable as follows:

$$\hat{R}_{AOI,t} = \alpha + \sum_{j=-J}^{+J} \beta_j \hat{R}_{SPI,t+j} + \sum_{j=-J}^{+J} \gamma_j D_{j,t} \hat{R}_{SPI,t+j} + \varepsilon_t \qquad (3)$$

Where $D_{j,t}$ is a binary dummy variable, taking the value of zero for observations in the pre-September 1990 period and the value of one for observations in the post-September 1990 period. The results of the model in (3) are reported in Table 4.

TABLE 4 ABOUT HERE

Table 4 indicates that the automation of the stock market has had a number of significant impacts on the information flow between the markets. First, the contemporaneous relation between the stock and futures markets significantly increases after automation. The response coefficient rises from 0.0736 before automation to 0.1306 after automation. This implies an increase of around 77% in contemporaneous information transfer after automation which supports our first hypothesis.

There is also support for the second hypothesis. The lag response coefficients at the first and second five-minute intervals have both substantially increased from 0.0288 to 0.0889 and 0.0248 to 0.0445 for the first and second lags, respectively. At the longer lags, we observe negative values on the dummy coefficients indicating a smaller information transfer again consistent with our second hypothesis. This finding is reinforced by the F-test which rejects the hypotheses that the lag dummy coefficient estimates are jointly equal to and sum to zero. In summary, there is a squeezing of information transfer from longer lags to shorter lags.

In contrast, there is little support for the third hypothesis. Whilst we observe negative values on the longer lead dummy coefficients, they are small in magnitude and not significant. Moreover, the short lead dummy coefficients are of the wrong sign to support the hypothesis. Indeed, these results indicate some mild evidence of a weaker feedback from the stock to the futures markets. However, the hypothesis that lead dummy coefficient estimates are jointly equal to zero and sum to zero is not rejected implying that there is no change in this relation after automation.

There are two possible explanations of this last result. First, it is feasible that automation has not altered the price discovery process in the spot market and indeed the open outcry auction performs equally well. If this explanation were accepted then we would also need to explain the significant increase in both the contemporaneous relationship and the futures lead. Various possibilities exist including a general improvement in, and lower cost of, gathering information over time, particularly in relation to macroeconomic information. Second, the introduction of automated trading may have indeed improved the price discovery process in the spot market. However, given the cheaper costs of trading in the futures market, traders extract (macro-based) information from the spot market and then trade index futures. Given our research design, we cannot completely discard either of these explanations. However, we note that the strong increase in the contemporaneous relationship is unlikely to be consistent with either argument.

Figure 2 provides a graphical representation of the results. This figure illustrates the magnitude of the response coefficients at various leads and lags highlighting differences in these coefficients before and after automation of the stock market. The increase in the information transfer from the futures to the stock market at short lags is most apparent together with the stronger contemporaneous relation.

FIGURE 2 ABOUT HERE

Table 5 summarises the change in the lead-lag relations before and after automation by rerunning the tests over a number of sub-periods. The table reports the contemporaneous and sum of the short-term (five- and ten-minute intervals) lag and lead coefficients. They show that, in all periods after automation, the sum of the first two lag coefficients is increased and becomes stronger over time. Further, the contemporaneous relation also increases monotonically over time. However, the lead coefficients show again some inconsistency.

TABLE 5 ABOUT HERE

The choice of window used in the analysis is somewhat arbitrary. Consequently the analysis was rerun using one-month, six-month and twelve-month windows either side of the automation date (September 1990) and the results were generally quite robust to different sample lengths.

5.3 Changes in Information Flow

The research design does not account for changes in either firm-specific or market-wide information flow. It is possible that changes over the period in the amount of information, timing of information arrival, mix of information between public and private and/or firm-specific and market-wide, may influence the findings. Private information is by definition unobservable. However, Chan (1992) proposes the construction of a variable (R) that measures the ratio between price movements in the stock and futures markets. To explain, consider the portfolio of N stocks within a stock index. If there is market wide information that is reflected in a price change (ΔS_i) of all index stocks, then the change in value of the futures contract is given by:

$$\Delta F = \left| \sum_{i=1}^{N} \Delta S_i \right| \tag{4}$$

Similarly the change in value of the portfolio of individual stocks is given by:

$$\Delta I = \sum_{i=1}^{N} \left| \Delta S_i \right| \tag{5}$$

Chan proposes a ratio:

$$R = \Delta F / \Delta I \tag{6}$$

such that R measures the extent of market wide movements. If all individual stocks experience a similar price change in the same direction due to market-wide information, R takes on the value of unity. When individual stock prices move in opposite directions the ratio is lower.

Chan (1992) notes that R is a price-weighted measure and can be unduly influenced by stocks with a large price. As an alternative, Chan proposes another variable to measure the extent of market-wide movement. This ratio (P) measures the net proportion of stocks moving together and is defined as:

$$P = \frac{\left| N_u - N_d \right|}{(N_u + N_d + N_z)} \tag{7}$$

where N_u is the number of stocks with a positive price change, N_d is the number of stocks with a negative price change and N_z is the number of stocks with zero price change.

From (7), if all stock prices move together then P takes on the value of unity. Conversely if stock prices move in opposite directions then P is less than unity.

The variables R and P both attempt to measure the comovement of stock prices which is assumed to be due to market-wide information. In this study, we are concerned not with the values of the ratios but rather with the relative values of the ratios pre- and post-automation of the stock market. To perform this comparison, we estimate R and P on a daily basis and break the sample at September 1990. Table 6 presents these results.

TABLE 6 ABOUT HERE

From Table 6, there is no significant difference in either ratio under both the parametric and non-parametric tests. Hence there is no support for a difference in the extent of market-wide movements pre- and post-automation. Thus, it is unlikely that the earlier findings are attributable to a systematic change in the mix of firm-specific and market-wide information over the period.

5.4 Lead-Lag Relation for Squared Returns

In this section we apply the earlier methodology to examine the lead-lag relation between squared returns. The squared returns are a proxy for volatility. A regression of squared AOI index returns on squared SPI futures returns enables an examination of whether the lead-lag volatility relation differs after automation. The regression is specified in (8) which is the counterpart to (3) and the results are presented in Table 7.

$$\left(\hat{R}_{AOI,t}\right)^2 = \alpha + \sum_{j=-J}^{+J} \beta_j \left(\hat{R}_{SPI,t+j}\right)^2 + \sum_{j=-J}^{+J} \gamma_j D_{j,t} \left(\hat{R}_{SPI,t+j}\right)^2 + \varepsilon_t \tag{8}$$

TABLE 7 ABOUT HERE

From Table 7 the results indicate that there is no volatility feedback in either direction at any lag either before or after automation, with the exception of a significant increased effect after automation at the fifth lag which can probably be regarded as spurious. All F-tests fail to reject (at 1%) the joint hypotheses of a changed effect after automation. These results indicate that the feedback between the markets is restricted to return innovations, rather than volatility innovations. An implication of these findings could be that the information transfer process is sign dependent. Indeed an argument could be mounted that the differential costs of trading a short versus a long position in the stock market may induce asymmetry in the feedback process. A test of this issue could condition the lead-lag relation on the sign of the return innovations but we leave this to further research.

6. CONCLUSION

This paper has examined the lead-lag relation between the stock and futures markets in Australia. This issue is of importance given the implications such relations for in assessing the information transfer between markets. The paper adds to the literature by examining the lead-lag relation over a period in which the stock market trading mechanism changed from floor-based trading to automated screen trading. By focusing on this period we are able to more directly examine the impact of the change in trading mechanism on information transfers between markets. The study utilises an intraday data set consisting of matched observations on the AOI and SPI indices.

The paper initially examines the general lead-lag relationship which has previously not been well-documented in Australia. We find evidence of a substantial information flow between the stock and futures markets. There is a contemporaneous relation, a feedback from the futures market to the stock market of around twenty minutes and a feedback of up to ten minutes from the stock market to the futures market.

After the introduction of automated trading of the stock market in September 1990, we find a significant change in the information transfer process. First, the contemporaneous relation between the markets is significantly increased consistent with the hypothesis that automated trading results in a richer and more timely information set which accelerates the price discovery process. Second, we find that the lead-lag relation becomes stronger at shorter lags and more unidirectional from the futures market to the stock market again consistent with the general hypothesis. However, our third expectation of a stronger feedback from the stock market to the futures market at short leads was not supported. Our study has not controlled for changes in the volume of information or the impact of private information which may offer an alternative explanation of our results. However, we find no evidence supportive of a change in the extent of market-wide information flow over the period.

Further, institutional changes over the period may confound the effect of automation. For example, the introduction of trading halts in the stock exchange in relation to firm-specific information is likely to have affected the relation between the markets.

The final part of the study examined volatility feedback between the markets and we found no evidence of feedback in either direction. This finding suggests further research in order to examine the impact of the sign of the return innovation on the information transfer process. Given the above caveats, the evidence suggests that the automation of the stock market has enhanced the information attributes of the Australian markets.

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Figure 1

All Ordinaries Index Stocks that Traded on SEATS: April 1989 to February 1992

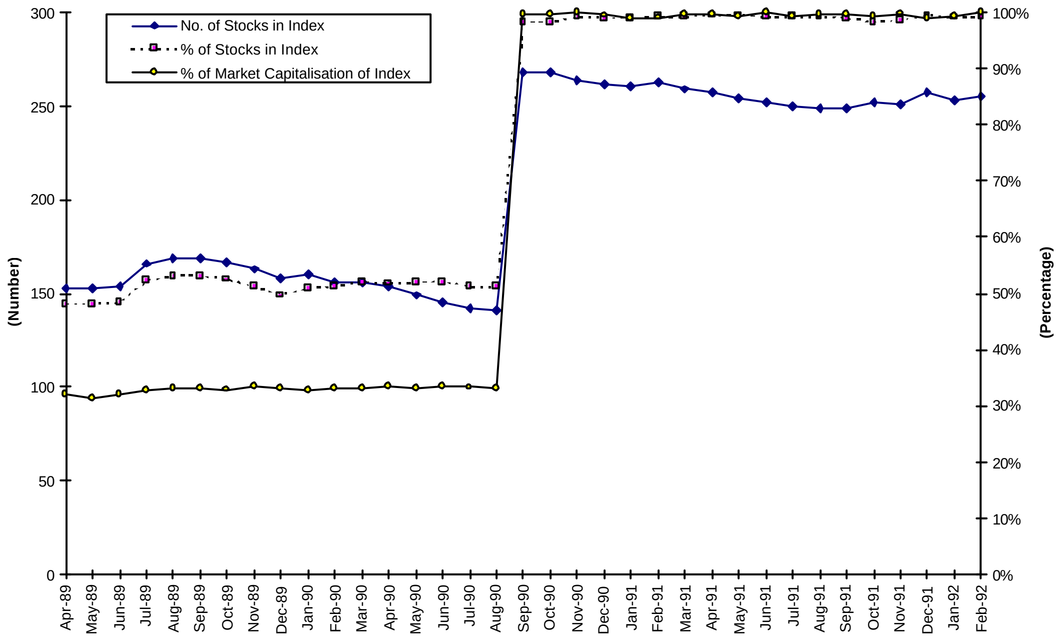

Figure 2

Information Response Coefficients

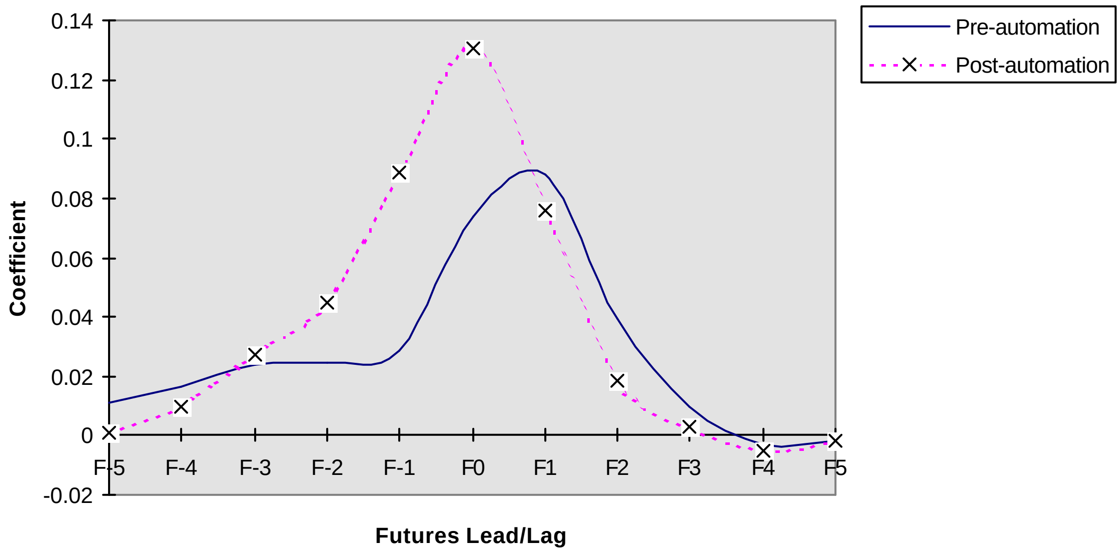

Table 1
Descriptive Statistics of AOI and SPI Returns
Five-minute intervals: April 1989 to February 1992

	AOI	SPI
Mean	0.716×10^{-5}	-0.092×10^{-5}
Standard Deviation	0.048×10^{-2}	0.113×10^{-2}
Minimum	-0.0079	-0.0168
Maximum	0.0187	0.0310

Table 2
Autocorrelation Coefficients of the AOI and SPI Returns
April 1989 to February 1992

Autocorrelation Coefficients	AOI Estimate	t-statistic	SPI Estimate	t-statistic
ρ_1	0.1855	30.78*	-0.1059	-17.21*
ρ_2	0.1437	23.86*	0.0463	7.43*
ρ_3	0.0497	8.39*	0.0179	2.95*
ρ_4	0.0236	4.15*	0.0160	2.69*
ρ_5	-0.0069	-1.48	-0.0079	-1.37
ρ_6	0.0036	1.34	-0.0031	-0.89
ρ_7	-0.0030	-1.14	-0.0174	-4.96*
ρ_8	-0.0062	-2.31*	0.0113	3.23*
ρ_9	0.0069	2.59*	-0.0017	-0.49
ρ_{10}	-0.0047	-1.79	-0.0109	-3.12*

* significant at 1%

Table 3
Parameter Estimates From Regression (2) of AOI Return Innovations on Lagged, Contemporaneous and Leading SPI Return Innovations

Parameter	Estimate	Standard error	t-statistic
α	0.5216E-5	0.2702E-5	1.93
β_{-5}	0.0063	0.0035	1.79
β_{-4}	0.0129	0.0036	3.56*
β_{-3}	0.0256	0.0038	6.66*
β_{-2}	0.0355	0.0046	7.69*
β_{-1}	0.0567	0.0059	9.61*
β_{0}	0.0998	0.0119	8.37*
β_{+1}	0.0832	0.0043	19.43*
β_{+2}	0.0298	0.0039	7.53*
β_{+3}	0.0058	0.0033	1.74
β_{+4}	-0.0043	0.0035	-1.22
β_{+5}	-0.0015	0.0030	-0.49

Hypothesis	F-statistic	p - value
$\beta_{-1}+\beta_{-2}+\beta_{-3}+\beta_{-4}+\beta_{-5}=0$	93.27	0.0000
$\beta_{-1}=\beta_{-2}=\beta_{-3}=\beta_{-4}=\beta_{-5}=0$	158.31	0.0000
$\beta_1+\beta_2+\beta_3+\beta_4+\beta_5=0$	151.61	0.0000
$\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=0$	36.48	0.0000

Notes: Standard errors are based on the White (1980) heteroscedasticity consistent covariance matrix.
* denotes significance at 1%

Table 4

Parameter Estimates From Regression in (3) of AOI Return Innovations on Lagged, Contemporaneous and Leading SPI Return Innovations Before and After Automation in September 1990

Parameter	Estimate	Standard error	t-statistic
α	0.52E-5	0.26E-5	1.97
γ_{-5}	-0.0100	0.0071	-1.41
β_{-5}	0.0111	0.0037	2.97*
γ_{-4}	-0.0063	0.0072	-0.87
β_{-4}	0.0163	0.0039	4.11*
γ_{-3}	0.0038	0.0076	0.49
β_{-3}	0.0236	0.0048	4.90*
γ_{-2}	0.0197	0.0088	2.23
β_{-2}	0.0248	0.0065	3.83*
γ_{-1}	0.0601	0.0105	5.70*
β_{-1}	0.0288	0.0083	3.47*
γ_{0}	0.0570	0.0223	2.54*
β_{0}	0.0736	0.0216	3.40*
β_{+1}	0.0877	0.0064	13.74*
γ_{+1}	-0.0116	0.0087	-1.33
β_{+2}	0.0392	0.0054	7.31*
γ_{+2}	-0.0210	0.0082	-2.55*
β_{+3}	0.0095	0.0041	2.33*
γ_{+3}	-0.0063	0.0066	-0.95
β_{+4}	-0.0031	0.0045	-0.70
γ_{+4}	-0.0022	0.0069	-0.32
β_{+5}	-0.0015	0.0034	-0.44
γ_{+5}	-0.0005	0.0061	-0.08

Hypothesis	F-statistic	p - value
$\gamma_{-1}+\gamma_{-2}+\gamma_{-3}+\gamma_{-4}+\gamma_{-5}=0$	9.917	0.0016
$\gamma_{-1}=\gamma_{-2}=\gamma_{-3}=\gamma_{-4}=\gamma_{-5}=0$	8.891	0.0000
$\gamma_{1}+\gamma_{2}+\gamma_{3}+\gamma_{4}+\gamma_{5}=0$	5.253	0.0219
$\gamma_{1}=\gamma_{2}=\gamma_{3}=\gamma_{4}=\gamma_{5}=0$	1.747	0.1201

Notes: Standard errors are based on the White (1980) heteroscedasticity consistent covariance matrix.
* denotes significance at 1%

Table 5

Lead-Lag of AOI and SPI Innovations Over Various Periods Surrounding Automation

	-17 to 0 months	-12 to -6 months	-6 to 0 months	0 to +6 months	+6 to +12 months	0 to +17 months
β_{-1} to β_{-2}	0.05366	0.05909	0.06213	0.10193	0.14103	0.13350
β_0	0.07356	0.04804	0.05880	0.12184	0.13633	0.13060
β_1 to β_2	0.12697	0.10800	0.14056	0.13411	0.07162	0.09438

Table 6
Estimates of Market-Wide Comovement Variables Before and After Automation in September 1990

	R	P
Mean value Pre-Automation April 1989 – August 1990	0.6228	0.4925
Mean value Post-Automation October 1990 – February 1992	0.5861	0.4544
t-test for differences in means	1.54	1.69
Wilcoxon-Mann-Whitney test Z-score	0.001	-0.001

Notes: The variables R and P are defined in equations (6) and (7) respectively in the text and are from Chan (1992).

Table 7
Parameter Estimates From Regression in (4) of AOI Squared Return Innovations on Lagged, Contemporaneous and Leading SPI Squared Return Innovations Before and After Automation in September 1990

Parameter	Estimate	Standard error	t-statistic
α	0.59E-7	0.53E-7	1.11
γ_{-5}	0.01684	0.00632	2.66*
β_{-5}	-0.00078	0.00121	-0.64
γ_{-4}	0.01505	0.00653	2.30
β_{-4}	-0.00032	0.00137	-0.23
γ_{-3}	-0.00079	0.00792	-0.09
β_{-3}	0.00013	0.00155	0.08
γ_{-2}	0.01387	0.01053	1.31
β_{-2}	0.00432	0.00612	0.70
γ_{-1}	0.01717	0.01560	1.10
β_{-1}	0.00122	0.00962	0.12
γ_{0}	-0.08806	0.11981	-0.73
β_{0}	0.11377	0.12063	0.94
β_{+1}	-0.00859	0.01714	-0.50
γ_{+1}	0.03186	0.02059	1.54
β_{+2}	-0.00060	0.00152	-0.39
γ_{+2}	0.03013	0.01604	1.87
β_{+3}	-0.00086	0.00183	-0.47
γ_{+3}	0.00018	0.00542	0.03
β_{+4}	0.00037	0.00095	0.38
γ_{+4}	-0.00129	0.00573	-0.22
β_{+5}	-0.00128	0.00182	-0.71
γ_{+5}	0.00207	0.00384	0.54

Hypothesis	F-statistic	p - value
$\gamma_{-1}+\gamma_{-2}+\gamma_{-3}+\gamma_{-4}+\gamma_{-5}=0$	5.991	0.0144
$\gamma_{-1}=\gamma_{-2}=\gamma_{-3}=\gamma_{-4}=\gamma_{-5}=0$	2.631	0.0219
$\gamma_1+\gamma_2+\gamma_3+\gamma_4+\gamma_5=0$	4.255	0.0391
$\gamma_1=\gamma_2=\gamma_3=\gamma_4=\gamma_5=0$	1.307	0.2573

Notes: Standard errors are based on the White (1980) heteroscedasticity consistent covariance matrix.
* denotes significance at 1%