

The Spurious Ratio Problem, Determinants and Impact of Long-term Debt Issuances¹

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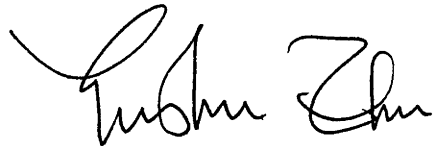
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Declaration

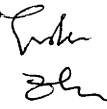
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Abstract

This thesis investigates the spurious ratio problem in capital structure studies, the determinants of capital structure, and price impacts of long-term debt issuances.

Essay 1 compares three models commonly adopted in the capital structure literature; a pooled time series cross-sectional regression model, a first differencing fixed effects regression model, and a dynamic system GMM panel model. We use the Monte-Carlo simulation method, as developed by Barraclough (2007), to give statistical inference for the above models. The simulation results suggest multiple regression models sharing common divisors suffer from a latent spurious ratio problem and the two panel models are more appropriate to test capital structure theories with variables in levels adopted instead of ratios. We observe that past realization of debt (one-year lag) explains most of the current debt level after controlling for endogeneity. Last, we find no significant associations between debt level and firm specific characteristics.

Essay 2 shows the probit model is free from the spurious ratio problem even when ratios are adopted in testing capital structure theories. Results indicate, contrary to stylized facts, that leverage increasing firms tend to be more profitable and firms with high R&D tend not to use debt as a means of financing.

Essay 3 investigates the price impact of long-term debt issuances using Heckman's (1979) two-step selection model. For Heckman's specification step, the matching firm approach of Barber and Lyon (1996) is implemented at size and industry dimensions. Although a significant *negative* cumulative abnormal return (CAR) is found, this price

impact is no longer significant once the self-selection factor is included. The insignificant price impact is robust to a range of different specifications including a number of different benchmarks used in calculating CAR.

Key words: Debt; Capital structure; Spurious ratio problem; Price impact; Endogeneity

JEL classification: G32; H20

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Chapter 1

Introduction

This thesis investigates the spurious ratio problem in capital structure studies, determinants of capital structure, and price impacts of long-term debt issuances. We show sharing common divisors in multiple regression models plagues previous studies, and address the problem using a variety of alternative models including first-differencing fixed effects panel models, system GMM models, and probit models. We also investigate the price impact of long-term debt issuances.

Essay 1 reinvestigates the relationship between financial leverage and firm characteristics by considering a spurious ratio issue that exists in previous studies of capital structure decisions. First, we show that ratio variables used in multiple regression analysis can lead to spurious inferences and this may account for some of the conflicting results observed in the literature. With a sample of US long-term debt issuances, we investigate the determinants of debt leverage by building a multiple regression model with proxies for asset structure, size, uniqueness, profitability and growth. These vari-

ables are commonly adopted in the literature and most of them are scaled by total asset value as a size adjustment. We argue that the scaling plagues traditional capital structure tests and induces the spurious ratio problem. Second, to avoid the spurious ratio problem and better capture the persistence feature and endogeneity issues of capital structure, we introduce a first differencing fixed effects panel model and a dynamic system GMM model, both using variables in levels instead of ratios. Our dynamic system GMM panel model results suggest that past realization of debt explains most of the current debt level after controlling for endogeneity; in addition, no association is found between debt level and firm specific characteristics after considering fixed effects and endogeneity.

Essay 2 addresses the estimation in a way that is free from the spurious ratio problem using a probit model. With modifications to the simulation technique developed by Barraclough (2007), the cut-off values are obtained. We observe no difference between these critical values and those of conventional levels. This observation suggests no spurious ratio problem is evident in our probit model, even though ratios are adopted. In addition, the probit model has fewer assumptions and is free from the concern of the spurious ratio problem. This model is more appropriate when investigating capital structure issues. Results indicate that leverage increasing firms tend to be larger and more profitable, and firms with high research and development expenditures (r&d) tend not to use debt as a means of financing.

Extending the work of Essay 1 and 2, Essay 3 aims to determine whether the long-term debt issue announcement affects a firm's ex post stock price by considering the

self-selection issue. We investigate the price impact of long-term debt issuances using Heckman's (1979) two-step selection model. For Heckman's specification step, the matching firm approach of Barber and Lyon (1996) is implemented at size and industry dimensions. Although a significant *negative* cumulative abnormal return (CAR) is found, this price impact is no longer significant once the self-selection factor is included. The insignificant price impact is robust to a range of different specifications including a number of different benchmarks used in calculating CAR. The zero price impact finding is consistent with Modigliani and Miller's (1958) irrelevance theory.

Chapter 2

The Spurious Ratio Problem and its Corrections

- Empirical Tests of Capital Structure

2.1 Introduction

Does the debt-equity choice which changes a firm's capital structure also affect a firm's performance? This question has been debated since the publication of Modigliani and Miller's (1958) irrelevance theory under the assumption of a frictionless world. In the real world however; the existence of frictions such as taxation and agency problems, etc., cast doubt on whether this theory holds. To date, there is no uniform answer as the empirical findings are mixed and conflicting. A cross-sectional multiple regression model is one commonly used approach to examine if ex ante firm characteristics affect financial leverage. However, even when this same approach accompanied with commonalities in the variables are used, the results of different studies are contradictory. For example, some researchers find a positive relationship between debt and profitability (such as MacKay and Phillips (2001), Frank and Goyal (2008)); while others find a negative relationship (Titman and Wessels (1988), Rajan and Zingales (1995), Baker and Wurgler (2002), Fama and French (2002), Faulkender and Petersen (2005)).

This chapter reinvestigates the relationship between financial leverage and firm characteristics by considering a spurious ratio issue that exists in previous studies of capital structure decisions. First, we show that ratio variables used in multiple regression analysis can lead to spurious inferences and this may account for some of the conflicting results observed in the literature. With a sample of US long-term debt issuances, we investigate the determinants of debt leverage by building a multiple regression model with proxies for asset structure, size, uniqueness, profitability and growth. These variables are commonly adopted in the literature and most of them are scaled by total

asset value as a size adjustment. We argue that the scaling plagues traditional capital structure tests and induces a spurious ratio problem.

Second, to avoid the spurious ratio problem and better capture the persistence feature and endogeneity issues of capital structure, we introduce a first differencing fixed effects panel model and a dynamic system GMM model respectively, both using variables in levels instead of ratios. Our dynamic system GMM panel model results suggest that past realization of debt explains most of the current debt level after controlling for endogeneity; in addition, no association is found between debt level and firm specific characteristics after considering fixed effects and endogeneity in this study.

The spurious ratio problem associated with multiple regression analysis was first noted by Pearson (1897). Pearson showed that in the case where three uncorrelated identically distributed random variables X , Y , Z have the same coefficient of variation (standard deviation divided by expected value), the expected correlation coefficient estimator between Y/Z and X/Z ¹ is 0.5 when in fact, the correlation between Y and X is 0. The contradictory results indicate that the coefficient estimators are biased in the model using ratios and hence, misleading inferences may be drawn. Kronmal (1993) further examines the spurious ratio problem and shows that the coefficient estimators are biased when ratios are used in dependent and independent variables.

In contrast to Pearson and Kronmal who focus on bias corrections in estimators,

¹Assuming the values of X , Y are two independent normally distributed random variables with expected value of 0 and variance of 1, then the ratio Y/X has a standard Cauchy distribution. The t-statistics are invalid when applying the Cauchy distribution. For example, the standard Cauchy distribution coincides with the Student's t-distribution with one degree of freedom. The t-value for one degree of freedom is 12.71 at the 5% confidence level, whilst 1.96 used in conventional statistical inference assuming infinity degrees of freedom.

Barracough (2007) introduces an alternative solution to this problem to improve statistical inference procedures. She uses a Monte-Carlo simulation technique to generate critical values for the coefficient slopes, the t-values and the adjusted R-squared estimates. The simulation based confidence intervals for t-values are then compared to conventional levels. The simulation results of Barracough (2007) show the critical values are higher than conventional levels for all the scenarios allowing for different levels of correlation between the set of X variables, the set of Z variables and cross-correlation between the X and Z variables². Therefore, significant associations may be concluded according to standard statistical inference whilst in fact, the correlations are spurious. In this study, we consider the spurious ratio problems and modify Barracough's simulation technique for testing different models. Consistent with Barracough (2007), we find the simulated confidence intervals for estimates have much wider ranges than those under conventional levels in the multiple regression models using ratios. In contrast, our results suggest no spurious ratio problem in the two panel models when using variables in levels instead of ratios; as the simulation based statistical inference is similar to conventional levels.

²In parallel with the above, we treat X, Y, Z as the independent variable vector, dependent variable and the common divisor vector.

2.2 Literature Review

2.2.1 Ratio regression models in capital structure studies

Capital structure theories attempt to explain whether firm value, in practice, can be optimized by managers' financial choices between debt and equity. Some studies suggest that the decision of debt issuance which leads to a higher leverage ratios, breaks the equilibrium of taxation benefit, bankruptcy cost, agency cost, and managerial entrenchment, etc. Consequently, the debt issuance decision may affect firm value. The earliest framework in this field is the irrelevance theory developed by Modigliani and Miller (1958). They show that in a world with no tax, the value of a firm and the average cost of funds from all sources are independent of leverage. Since then, numerous empirical studies have attempted to test if the conclusion still holds in a world with taxes and other frictions. There are three dominant theoretical explanations: trade-off (Kraus and Litzenberger, 1973), pecking-order (Myers and Majluf, 1984) and market timing theory (Baker and Wurgler, 2002). Empirically, the most common methodology used is performing a regression between the leverage ratio (book, market leverage or leverage differences) and firm characteristics such as assets tangibility, firm size, profitability, uniqueness, and growth to assess how these characteristics affect a firm's financial leverage. In practice, these proxies along with debt are adjusted for size by scaling by the book value of total assets (or sales, the market value of total assets). However, we argue that this adjustment for firm size causes a spurious ratio problem as first documented more than a hundred years ago by Pearson (1897). Capital structure

has continued to puzzle researchers and there is yet no consensus regarding how a firm's characteristics affect debt leverage³. In this chapter, we select five (three of them are ratios) out of the 39 factors examined by Frank and Goyal (2003); which they classify as Tier 1 and Tier 2 robust factors:

a. Asset structure The conventional prediction on a **positive** sign of tangibility that more tangible assets are associated with more collateral and thus higher leverage (Rajan and Zingales (1995), Baker and Wurgler (2002), Faulkender and Petersen (2005)). However, Harris and Raviv (1991) report a **negative** sign for tangibility and argue that firms with few tangible assets may bear more asymmetric information costs and thus tend to accumulate more debt and hence higher leverage over time. Leary and Robert (2005) examine debt issuances and also find a **negative** influence of tangibility. In contrast, Titman and Wessels (1988) find the asset tangibility factor is insignificant.

b. Size Larger firms are generally more diversified, having relatively easier access to debt markets and lower financial distress cost, thus tends to be higher leveraged. In general, a **positive** relationship is expected between leverage and firm size (Titman and Wessels (1988), Frank and Goyal (2003) and Faulkender and Petersen (2005)).

c. Profitability The trade-off theory predicts that profitable firms will issue more debts to maximize tax benefits (e.g. MacKay and Phillips (2001), Frank and Goyal (2008)). On the other hand, Ross (1977) develops an asymmetric information

³Note, most of the studies apply the multiple regression method.

model and states that more profitable firms may face lower asymmetry costs when borrowing, thus they are able to borrow more. As a comparison, however, the majority of findings detect a **negative** relation between profitability and debt leverage (Titman and Wessels (1988), Rajan and Zingales (1995), Baker and Wurgler (2002), Fama and French (2002)). In line with the pecking-order theory, a recent paper by Faulkender and Petersen (2005) use sales instead of total assets as the divisor of the ratio variables and conjecture that profitable firms are reluctant to use debt unless their internal funds are exhausted due to asymmetric information costs, thus lower leverage is expected.

d. Uniqueness Titman, et al. (1988) and Faulkender, et al. (2005) find a significant **negative** relation between leverage and Research and development expenditure (thereafter, r&d) scaled by sales (uniqueness factor). They interpret the inverse relationship as: firms with more r&d suffer from higher financial distress and thus, will use less debt. This interpretation is in line with the trade-off theory. However, Shyam-Sunder and Myers (1999) use variables in levels instead of ratios in a regression model, and find r&d is **positively** related to leverage. They conclude that increasing r&d will enlarge a firm's financing deficit, and hence, financial deficit is **positively** correlated with leverage according to pecking order theory.

e. Growth The empirical literature shows a mixed pattern of the market-to-book ratio (growth factor), with most studies finding the market-to-book ratio negatively relates to leverage (Rajan and Zingales (1995), Baker and Wurgler (2002), Goyal, et al. (2003), Faulkender and Petersen (2005)). Myers (1977) suggests a high market-

to-book ratio is associated with more future growth opportunities. Based on pecking order theory, equity funding is more costly than debt due to information asymmetry. Therefore, high growth firms may be reluctant to issue equity even when they have to pass up optimal investment opportunities, and thus, high leverages are expected.

The above gives a summary of contradictory conclusions on the relationship between financial leverage and firm characteristics; these contradictions occur even when there are commonalities in the variables and research method. We argue the spurious ratio problem documented by Barraclough (2007) helps to explain why conflicting results have previously been observed.

2.2.2 Panel data models in capital structure studies

A number of studies suggest that even if a firm has a target capital structure, the target may not be static, but evolves with the firm's history (e.g. Fischer, et al. (1989), Harris and Raviv (1991), Shyam-Sunder and Myers (1999), Goldstein and Leland (2001), Kayhan and Titman (2007), etc.). Panel data models can improve the efficiency of econometric estimates as they integrate the time-varying features, in sense of a firm's history, whilst cross-sectional models fail on this point.

Previous studies find a firm tends to keep stable capital structure despite the evidence of moving toward more moderate levels of debt leverage. Lemmon, et al. (2008) find that firms tend to maintain their financial leverage levels of over 20 years. In addition, they report a R-squared of 60% using a fixed effects panel regression model. The

R-squared value suggests unobservable fixed effects are able to explain more than half of a firm's debt leverage. We consider the fixed effects with using a first differencing approach.

In addition to fixed effects, Ozkan (2001) suggests the shocks affecting a firm's capital structure decision are also influencing its firm characteristics. To address the simultaneity problem which as one form of endogeneity, Ozkan uses a first-differenced GMM (Generalized Method of Moments) method developed by Arellano and Bond (1991), with an unbalanced panel sample of UK firms. However, Ozkan's model suffers from the latent spurious ratio problem due to using ratios. We show that a dynamic system GMM model acts as a better tool than a first-differenced GMM model to address endogeneity issues; whilst overcoming the weak instruments problem and the problem of too many instruments.

2.3 Data

Some studies include both public straight and convertible long-term debt resulting in larger sample sizes than the sample of public straight debt issuances only. However, earlier survey studies suggest that issuers generally regard convertible debt as a delayed equity offering (e.g. Pilcher (1955), Brigham (1966), and Hoffmeister (1977)). Therefore, it is inappropriate to include convertible debt in the sample. In addition, several studies include both public and private long-term debt, however, the offering dates are not publicly ascertained for private debts which weakens data reliability. Further, a number of studies focus on debt maturity by considering short and long-term

debt as substitutes, contrary to previous studies which examine the substitution effects between equity and debt.

This study focuses on leverage increases that are caused by public straight long-term debt issuances. In doing this, our research purpose is better defined, even though the sample size is smaller. The sample inclusion is in line with our initiative to compare our results to those of equity-debt substitutes studies, while at the same time problems in sample selection can be avoided.

A number of data selection criteria are imposed. First, we only include issuers of publicly issued straight debts with maturity of more than one year from the SDC platform during the sample period of 1986-2006. Issuances without announcement information are excluded. Second, firms without financial information on the Compustat or price information on the CRSP are excluded. Third, firms in a regulated utility or a financial sector with the SIC codes of 4900-4999 and 6000-6999 are excluded since these firms are very different from their industry counterparts in terms of both assets structure and funding sources. Fourth, firms with missing information on total assets, sales, share outstanding and share price for the fiscal year-end prior to the debt offerings are deleted. Fifth, to eliminate the possible impacts of other events within the firms, issuers with any of the following events occurring 30 calendar days before and after the announcement dates of debt offerings are excluded: ordinary share issue, convertible bond issue, stock split, share repurchase, and merger & acquisition. Sixth, companies issuing straight long-term debt more than once during the same fiscal year are excluded. This exclusion is because; with two consecutive debt announcements

occurring in the same financial year it is difficult to isolate the joint effect of these events. After imposing all the selection criteria, the final cross-sectional time series sample consists of 719 debt issue observations from 454 firms which is used in Section 2.3; and an unbalanced panel data sample of 6864 observations from the same 719 issuing firms during 1986-2006 are used in Section 2.4.

[Table 2.1 about here]

Table 2.1 presents summary statistics on the variables and these statistics are then compared with the estimations on all firms which are obtained from the Compustat without imposing our selection criteria (thereafter 'all Compustat sample'). The median of sales in our sample is US\$2,093 million, which is much higher than those of 'all Compustat sample'. This size difference suggests larger firms have relatively easier access to public debt markets, consistent with previous studies (Frank and Goyal (2008)). Similar patterns are also observed in other variables. For instance, the book leverage (market leverage) ratio is 56% (36%) in our sample and is 38% (24%) in the 'all Compustat sample', confirming the finding of Lemmon (2002) that financially unconstrained firms have higher debt capacities, thus they primarily use debt to meet their deficits while constrained (normally small, high-growth) firms issue more equity.

2.4 Multiple Regression Models Using Ratios

2.4.1 Multiple ratio regression model set-ups

To examine the spurious ratio problem in the regression models, two static regression models (Model 2.1 and 2.2) are used. Given the empirical evidence in the literature, the models posit that leverage (book leverage or market leverage) of a public company is determined by its firm characteristics of assets structure, size, uniqueness, profitability and growth.

Model 2.1: the Book-leverage regression model

$$\frac{d_i}{ta_i} = b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r\&d_i}{s_i} + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + v_i \quad (2.1)$$

Model 2.2: the Market-leverage regression model

$$\frac{d_i}{mva_i} = b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r\&d_i}{s_i} + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + \varepsilon_i \quad (2.2)$$

Where

– d_i denotes the book value of total debt;

– ta_i is the book value of total assets;

– ppe_i is the value of net property, plant and equipment;

– s_i represents net sales;

– $r\&d_i$ is research and development expenditure;

– $ebitda_i$ is operating income before depreciation;

$-mva_i$ is market value of assets, calculated as the book value of total assets less book value of equity plus market value of equity, and

$-v_i, \varepsilon_i$ are the error terms, with mean 0 and identically independently distributed.

2.4.2 The Monte-Carlo simulation based statistical inference for financial leverage regression models

We follow the Monte-Carlo simulation technique developed by Barraclough (2007); in which the Y variable has zero associations to X and Z variables, and the actual cross-correlations between X and Z variables which obtained from the actual sample are kept. Our Monte-Carlo simulation procedures are shown as following:

Step 1: To integrate the characteristics of issuing firms, the means (μ_Y, μ_X and μ_Z), standard deviations, and cross correlations of all variables are calculated based on the actual sample and are used as input values in our simulation. The simulated X, Y and Z variables are generated using:

$$Y_i = \mu_Y + \delta_i,$$

$$X_i = \mu_X + \gamma_i; \quad \text{and}$$

$$Z_i = \mu_Z + \xi_i$$

The error terms for X and Z (γ_i and ξ_i) are drawn from a multiple normal distribution with a mean value of 0, variance covariance matrix of V_{XZ} is based on an actual sample

as follow:

$$V_{XZ} = \begin{vmatrix} \sigma_{ppe}^2 & & & & & \\ \sigma_{ppe, rnd} & \sigma_{rnd}^2 & & & & \\ \sigma_{ppe, ebitda} & \sigma_{rnd, ebitda} & \sigma_{ebitda}^2 & & & \\ \sigma_{ppe, \ln(s)} & \sigma_{rnd, \ln(s)} & \sigma_{ebitda, \ln(s)} & \sigma_{\ln(s)}^2 & & \\ \sigma_{ppe, \ln(ta)} & \sigma_{rnd, \ln(ta)} & \sigma_{ebitda, \ln(ta)} & \sigma_{\ln(s), \ln(ta)} & \sigma_{\ln(ta)}^2 & \\ \sigma_{ppe, \ln(mva)} & \sigma_{rnd, \ln(mva)} & \sigma_{ebitda, \ln(mva)} & \sigma_{\ln(s), \ln(mva)} & \sigma_{\ln(ta), \ln(mva)} & \sigma_{\ln(mva)}^2 \end{vmatrix}.$$

Note that the natural logarithm of Z ($\ln(Z)$) is used and then exponentiated to obtain its value in level. The rationale is to avoid the simulation generating a negative value for **ta**, **mva** and **s**.

The error terms of the Y variable are drawn from the normal distribution with mean value of 0 and variance of σ_Y^2 which is independent of X and Z. Further, a treatment to obtain symmetric critical intervals is to replace the mean of Y variable by zero.

Step 2: 10, 000 simulation runs are performed. The simulated results on White (1980) corrected t-values, intercepts, and adjusted R-squared values are recorded for each simulation run and ranked according to their values.

Step 3: The critical values for the t-statistics are within the range of the 2.5 and 97.5 percentiles that correspond to tests of significance at the two-tail 5% probability levels. For the adjusted R-squared, the 95th percentile adjusted R-squared is reported as the 5% cut-off R-squared value. Any estimate values located within the boundary of critical t-statistics is regarded as insignificant from zero.

2.4.3 Simulation based statistical inference and results

[Table 2.2 about here]

Panels A-1 and B-1 of Table 2.2 report the cut-off values for the book and market leverage regression models at the 95% confidence intervals respectively. In Panel A-1, for instance, the cut-off t-values for coefficients range from the narrowest of $[-1.31, +1.29]$ (ppe/ta) to the widest of $[-11.38, 12.2]$ (Intercept), the corresponding t-statistics for (mva/ta) ranges from $[-2.34, +2.34]$, in contrast to $[-3.51, +3.46]$ observed in (ebitda/ta). The results are similar to Barraclough's (2007) in that the coefficient slopes are far from zero; the critical t-statistics are higher than the standard level of $[-1.96, +1.96]$ in well specified regression models. Noticeably, the adjusted R-squared is required to exceed 63% to be significant at the equation level. Similar findings are observed in the market-leverage model of Panel B-1.

Panels A-2 and B-2 of Table 2.2 show the results of Model 2.1 and 2.2 using the actual pooled cross-sectional sample. In Model 2.1 (the book-leverage regression mode), neither **asset structure** (ppe/ta) nor **uniqueness** (r&d/s) variables are significant when compared to the simulation based boundaries in Panel A-1 and B-1, even though they are significant under conventional levels. In addition, all the adjusted R-squares obtained from the regressions are lower than their corresponding critical values. Compared with Lemmon, et al. (2008) who report the adjusted R-squared ranges from 18% to 29% in traditional leverage regression models, our market leverage regression models appear to 'outperform' the traditional models, even though they are statistically insignificant. **Tangibility** and **uniqueness** are both negatively significant in the book

leverage model, which is consistent with Leary and Roberts (2005) and Faulkender and Petersen (2005); whilst, these two characteristics appear to be insignificant in Model 2.2 (the market-leverage model). In contrast, profitability and growth exhibit opposite results. However, the two variables are found negatively significant in the market leverage model and no significance is observed in the book leverage model, which is consistent with Leary and Roberts (2005) and Faulkender and Petersen (2005). Profitability and growth also insignificant in the market leverage model. Profitability and growth exhibit the opposite results; as they are found to be negatively significant in the market leverage model, no significance is observed in the book leverage model. In summary, the results in Table 2.2 exhibit strong evidence of the spurious problem in regression models using ratios, as pointed out by Pearson (1897), Kronmal (1993) and Barraclough (2007). Therefore, alternative models should be considered to overcome the spurious problem.

2.5 Panel Models Using Levels

We address the spurious ratio problem by two panel models, in which variables in levels instead of ratios are used. In addition, fixed effects are considered in both panel regression models and specifically, a dynamic system GMM model (hereafter, system GMM) is used to address endogeneity issues.

To show variables in levels will not result in the spurious ratio problem, we generate critical values using simulated dynamic panel data (DPD) for both panel models (Equation 2.3 and 2.4) with modifications to the Monte-Carlo simulation procedures de-

veloped by Barraclough (2007). The modification is made on generating an unbalanced panel data of 6864 observations (719 firm for 21 years); in which these observations are grouped by firm identification and time to reflect sample data's panel setting.

2.5.1 The first-differencing fixed effects panel model and results

$$Y_{it} = \alpha_i + X_{it}\beta + \varepsilon_{it}, \quad t = 1, \dots, T \quad (2.3)$$

Where

– Y_{it} denotes the book value of debt;

– α_i presents a vector of time-constant unobserved effects for each firm and it is arbitrarily correlated with the X_{it} term;

– X_{it} denotes the vector of explanatory variables: ppe, s, r&d, ebitda, mva; and the intercept term.

– ε_{it} is the error term, with mean 0 and uncorrelated to all Xs.

We first implement the first differencing transformation within firm to eliminate the time-invariant unobserved effects (α_i); and then apply the OLS estimation method.

[Table 2.3 about here]

Panel A-1 of Table 2.3 reports the simulated critical values for Model 2.3; all the slope coefficients for X variables are close to the true value of 0, with the t-values ranging from [-1.97, +1.98] (Difference of ppe) to [-2.23, +2.23](Difference of sales) which are close to the conventional 95% confidence level of [-1.96, +1.96].

Panel A-2 of Table 2.3 shows the result of Model 2.3 (the first-differencing fixed effects panel model) using the actual panel data sample. Results suggest that the value differences on collateral asset, sales, and r&d in levels are *positively* correlated to the difference on debt for every two adjacent years within firm. These findings can be linked to practice: we expect to see expanding size (total assets value), increasing collateral assets value (more asset purchasements) and more fund available to spend on r&d are associated with more debt initiatives in a firm.

2.5.2 The dynamic system GMM panel model and results

We now move to a dynamic system GMM panel model. Again, to identify the spurious ratio problems, we employ the same Monte-Carlo simulation technique in Section 2.3. To address the concern that explanatory variables are not strictly exogenous, we use the dynamic system GMM model developed by Blundell and Bond (1998) which also includes fixed effects.

$$Y_{it} = \alpha Y_{i,t-1} + X_{it}\beta + u_i + \epsilon_{it}, \quad |\alpha| < 1; \quad (2.4)$$

$$X_{it} = \rho X_{i,t-1} + \nu_{it},$$

for

$$i = 1, \dots, N; \quad t = 2, \dots, T.$$

Where

$-Y_{it}$ denotes the book value of debt;

$-u_i$ presents a vector of time-constant unobserved effects (fixed effects) across firms;

$-X_{it}$ denotes a vector of intercept term and explanatory variables: ppe, s, r&d, ebitda, mva;

X_{it} may be correlated or uncorrelated with u_i ;

X_{it} may be endogenous, predetermined or strictly exogenous with regard to ϵ_{it} ;

$-\epsilon_{it}$ and ν_{it} are the error terms which with mean 0 and uncorrelated to X variables.

Panel B-1 of Table 2.3 reports the simulated t-values range from the narrowest of [-1.968, 2.073] (one-year lagged debt, L.D) to the widest of [-2.076, +2.027] (research and development expenditure, r&d) The simulation based critical values are close to conventional interval of [-1.96, +1.96] which suggests no spurious ratio problem in the dynamic system GMM model using variable levels.

Panel B-2 of Table 2.3 shows Model 2.4 results; the lagged Debt variable is significant with a correlation coefficient of 0.93 and the corresponding t-value of 24.57; size (s) with a slope coefficient of 0.02, t-value of 2.10 is significant at the 95% level. It suggests the past realization of debt levels explain most of current debt levels and once the lagged debt term is added as explanatory variable, other firm characteristics are either insignificant (ppe, r&d, ebitda, mva, according to their t-values) or has minor effect (s, according to the slope coefficient). Our result suggests there is no significant relationship between debt and firm characteristics once endogeneity is controlled for⁴.

⁴The STATA code for GMM developed by Roodman (2006) not only provides estimation but

2.6 Conclusion

This study explores the spurious ratio problems caused by sharing common divisors in multivariate regression models evidenced in the capital structure literature. Without correction, the over-estimated t-values and R-squares under traditional statistical inferences can be misleading evidence of significant association between independent and dependent variables. In order to shed light on this problem, we show how the Monte-Carlo simulation technique developed by Barraclough (2007) provides reliable statistical inferences when the parametric conventional inference is invalid.

We further apply the same simulation procedures to two panel models using variables in levels instead of ratios, and no spurious ratio problem is evident. These two models are more appropriate to investigate capital structure theories after we considering the persistence character of capital structure (fixed effects) and endogeneity problems respectively. Results show changes on collateral assets, size, and r&d are positively associated to changes on debt values in the first differencing fixed effects model; and past debt level and size explain most of current debt level in the dynamic system GMM model which suggests no significant relationship between debt level and firm characteristics.

also built-in a series of tests including the correction method suggested by Windmeijer (2005) for cluster-robust errors to address the weak instrument problem. We follow Bond's (2002) and use the instruments of 3rd lagged variables in the differenced equations and the 4th lagged variables in the level equations and then moderate number of instruments to 32. (see Table 2.3 for related statistics tests)

Table 2.1 Sample descriptive statistics

Panel A: Variable composition		
Symbol	Name	Compustat data item
1.s	Sales	SALE
2.ppe	Propert,plant &equipment	PPENT, if missing then use PPEGT
3.mva	Market value of assets	AT-(AT-LT-PSTKL+TXDITC+DCVT)+CSHO*PRCC_F
4.r&d	Research & Development expenditures	RDIP
5.ebitda	Operating income before depreciation	OIBDP
6.d	Total debts	AT-(AT-LT-PSTKL+TXDITC+DCVT)
7.ta	Total assets	AT

Panel B: Comparison of summary statistics for our sample firm-year and all Compustat firm-year (1985-2005)

Our sample		(Million US\$)				All Compustat sample				(Million US\$)	
Variable	Mean	Median	Std Dev	Num. of obs	Variable	Mean	Median	Std Dev	Num. of obs		
1.s	5287	2093	8614	719	1.s	1111	93	6117	94060		
2.ppe	1859	722	3385	719	2.ppe	407	17	2484	94060		
3.mva	9330	3183	19835	719	3.mva	2102	142	14611	94060		
4.r&d	110	0	404	719	4.r&d	26	0	220	94060		
5.ebitda	764	297	1277	719	5.ebitda	160	8	1026	94060		
6.d	2930	1138	4907	719	6.d	751	34	7396	94060		
7.ta	4947	2039	8577	719	7.ta	1234	90	9373	94060		

Note: We require both samples have positive and no missing data on compustat AT (total asset), SALE (sales), PRCC_F (share price), CSHO (outstanding share numbers); Research &Development values are missing for about 2/3 of the samples; and we replace these missing values with 0.

Panel C: Cross-correlation of variables for cross-sectional sample

Variable	ppe	ln(s)	r&d	ebitda	ln(ta)	ln(mva)
ppe	1					
ln(s)	0.53	1				
r&d	0.29	0.34	1			
ebitda	0.8	0.63	0.62	1		
ln(ta)	0.63	0.9	0.37	0.69	1	
ln(mva)	0.58	0.88	0.41	0.71	0.96	1
d	0.74	0.61	0.59	0.85	0.69	0.66

Note: We use ln(S), ln(TA) and ln(MVA) instead of S, TA, MVA in the simulation to ensure these variable values are positive.

Table 2.2: Monte-Carlo simulation based inference for financial-leverage regression models and actual model results

Panel A-1: Book-leverage ratio regression model

$$\frac{d_i}{ta_i} = b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r \& d_i}{s_i} + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + v_i$$

Prob.level	Intercept		ppe/ta		ln(s)		r&d/s		ebitda/ta		mva/ta		R-squared
	b0	t(b0)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	b5	t(b5)	
2.50%	-11.38	-2.42	-1.31	-3.23	-1.38	-2.45	-4.66	-3.3	-3.94	-3.51	-1.64	-2.34	0.63
97.50%	12.2	2.49	1.29	3.22	1.34	2.4	4.66	3.32	3.92	3.46	1.61	2.34	

Panel A-2: Actual results of the book-leverage ratio regression model

61.96***	14.89	-5.76*	-1.78	0.43	0.77	-101.93***	-3.24	-24.19	-1.64	1.51	0.96	0.02
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Panel B-1: Market-leverage ratio regression model

$$\frac{d_i}{mva_i} = b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r \& d_i}{s_i} + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + \varepsilon_i$$

Prob.level	Intercept		ppe/ta		ln(s)		r&d/s		ebitda/ta		mva/ta		R-squared
	b0	t(b0)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	b5	t(b5)	
2.50%	-10.78	-2.48	-1.08	-3.11	-1.2	-2.48	-4.37	-3.41	-3.66	-3.61	-1.31	-2.29	0.66
97.50%	10.36	2.46	1.11	3.11	1.2	2.47	4.25	3.34	3.73	3.63	1.32	2.38	

Panel B-2: Actual results of the market-leverage ratio regression model

70.21***	20.74	-1.27	-0.51	-0.07	-0.18	-22.1	-1.12	-58.08***	-5	-10.36***	-10.14	0.44
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Note: 1. replication runs=10,000 number of observations for each simulated dataset: n=719.
2.d denotes the book value of total assets; ppe is the value of net property, plant and equipment; s is net sales; r&d is research & development expenditure; ebitda is operating income before tax; mva is market value of assets; v and ε are error terms.

Table 2.3: Monte-Carlo simulation based inferences for the first-differenced fixed effects and dynamic system GMM panel model

Panel A-1: The first-differenced fixed effects panel regression model

Prob.level	D.PPE		D.S		D.RND		D.EBITDA		D.MVA	
	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	b6	t(b6)
2.50%	-0.046	-1.97	-0.009	-2.23	-0.338	-1.97	-0.109	-1.97	-0.006	-2.2
97.50%	0.047	1.98	0.009	2.23	0.342	2.01	0.11	2.01	0.006	2.25

Panel A-2: The first-differencing fixed effects model results using actual sample

0.793***	8.20	0.138***	3.08	0.844***	2.63	-0.211	-1.15	0.007	1.19
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Panel B-1: The dynamic system GMM panel model

Prob. level	Intercept		L.Debt		PPE		SALE		RD		EBITDA		MVA	
	b0	t(b0)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	b5	t(b5)	b6	t(b5)
2.50%	-696.851	-2.049	-0.024	-1.968	-0.077	-2.05	-0.011	-2.073	-0.461	-2.076	-0.231	-1.986	-0.007	-2.011
97.50%	679.518	1.999	0.025	2.073	0.074	1.979	0.011	2.015	0.453	2.027	0.239	2.064	0.008	2.076

Panel B-2: The dynamic system GMM panel model results using actual sample

1.733	0.02	0.932***	24.57	0.037	0.78	0.024	2.1***	-0.153	-0.4	0.383	0.287	0.006	0.023
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Arellano-Bond test for AR(1): Z-value=-5.02	Sargan test of overid. Chi2(6)=182.53	Num. of Instruments=32
Arellano-Bond test for AR(2): Z-value=0.70	Hansen test of overid. Chi2(6)=9.39	

Note: replication times=10,000 Number of observations=6864

Chapter 3

The Determinants of Capital Structure

3.1 Introduction

Capital structure theories attempt to explain whether firm value, in practice, can be optimized by managers' financial choices between debt and equity. A majority of previous studies adopt multiple regression models to investigate the relationship between debt leverage (using either leverage level or leverage change) and firm characteristics, however, findings are mixed and conflicting. In Chapter 2, we concluded the spurious ratio problem may account for the conflicting empirical results. Pearson (1897) and Kronmal (1993) point out the spurious relation may arise in multiple regression models sharing common divisors. They caution against using ratios in multiple regression models as conventional statistical inference is not able to specify the bias caused by sharing

common divisors. Barraclough (2007) attempts to address the problem by modifying the conventional statistical inference method rather than correcting the biases. Hence, even though the estimates are biased, Barraclough's Monte-Carlo simulation method is still able to provide correct statistical inference for estimates when the spurious ratio problem occurs.

In Chapter 2, we first built two regression models using proxies for asset structure, size, uniqueness, profitability and growth as explanatory variables to explain a firm's financial leverage¹. Noticeably, most of the proxies are scaled by total assets value as a size adjustment. Secondly, we used Barraclough's (2007) simulation technique to provide cut-off values for slopes, t-values and R-squares estimation. Results show that the simulation based confidence intervals for t-values are much wider than conventional levels; and the significance level for R-squared has to be as high as 60%, which far exceeds the R-squared from traditional leverage regression models². However, these firm characteristics can show a significant association to debt leverage if conventional statistical inference is applied. As a result, we confirm the existence of a spurious ratio problem as documented by Pearson, Kronmal, and Barraclough. Finally, we introduced two panel models and showed that once variables in levels are used instead of ratios, the simulation based cut-off values are close to those of conventional statistical inference. This evidence suggests no spurious ratio problem once common divisors are dropped. However, using levels instead of ratios induces another problem: it changes the setting

¹These variables are commonly adopted in the capital structure literature; for example, Frank and Goyal (2003).

²The R-squared values from our sample are 1.5% and 44% for the book leverage model and the market leverage model respectively; and they are both insignificant at the equation level according to the simulation based cut-off values. In addition, Lemmon, et al. (2008) finds that the adjusted R-squares from traditional leverage regression models range from 18% to 29%.

of the models, so that, the results are not comparable to those from previous studies using ratios.

We address the estimation in a way that is free from the spurious ratio problem by using a probit model. With modifications to the simulation technique developed by Barraclough (2007), the cut-off values are obtained. We observe no difference between these critical values and those of conventional levels. This observation suggests no spurious ratio problem is evident in our probit model, even though ratios are adopted. In addition, the probit model has fewer assumptions and is free from the concern of the spurious problem, and consequently this model is more appropriate when investigating capital structure issues. Results indicate that, contrary to stylized facts, leverage increasing firms tend to be larger and more profitable, and firms with high research and development expenditures (r&d) tend not to use debt as a means of financing.

3.2 Literature Review

3.2.1 Ratio regression models in capital structure studies

Some capital structure studies suggest that the decision of debt issuance leads to a higher leverage ratio and breaks the equilibrium of taxation benefit, bankruptcy cost, agency cost, and managerial entrenchment etc. Consequently, the debt issuance decision may affect firm value. The earliest framework in this field is the irrelevance theory developed by Modigliani and Miller (1958). They show that in a world with no tax, the value of a firm and the average cost of funds from all sources are independent of

debt leverage. Since then, numerous empirical studies have attempted to test if the conclusion still holds in a world with taxes and other frictions. There are three dominant theoretical explanations: trade-off (Kraus and Litzenberger, 1973), pecking-order (Myers and Majluf, 1984) and market timing theory (Baker and Wurgler, 2002). Empirically, the most common methodology used is performing a regression between the leverage ratio (book, market leverage or leverage differences) and firm characteristics such as assets tangibility, firm size, profitability, uniqueness, and growth to assess how these characteristics affect a firm's financial leverage. In practice, these proxies along with debt are adjusted for size by scaling by the book value of total assets (or sales, the market value of total assets). However, we argue that this adjustment for firm size causes a spurious ratio problem as first documented more than a hundred years ago by Pearson (1897). Capital structure has continued to puzzle researchers and there is yet no consensus regarding how a firm's characteristics affect debt leverage³. In line with Chapter 2, we select five (three of them are ratios) out of the 39 factors examined by Frank and Goyal (2003); in which are classified as the Tier 1 and Tier 2 robust factors.

a. Asset structure Among all the main hypotheses, there is a conventional prediction on a **positive** sign of tangibility that more tangible assets are associated with more collateral and thus higher leverage (e.g. Rajan and Zingales (1995), Baker and Wurgler (2002), Faulkender and Petersen (2005)). However, Harris and Raviv (1991) report a **negative** sign for tangibility and argue that firms with few tangible assets may bear more asymmetric information costs and thus tend to accumulate more

³Note, most of the studies apply the multiple regression method.

debt and hence higher leverage over time. Leary and Robert (2005) examine debt issuances and also find a **negative** influence of tangibility. In contrast, Titman and Wessels (1988) find the asset tangibility factor is insignificant.

b. Size Larger firms are generally more diversified, having relatively easier access to debt markets and lower financial distress cost, thus tends to be higher leveraged. In general, a **positive** relationship is expected between leverage and firm size (Titman and Wessels (1988), Frank and Goyal (2003) and Faulkender and Petersen (2005)).

c. Profitability The trade-off theory predicts that profitable firms will issue more debts to maximize tax benefits (e.g. MacKay and Phillips (2001), Frank and Goyal (2008)). On the other hand, Ross (1977) develops an asymmetric information model and states that more profitable firms may face lower asymmetry costs when borrowing, thus they are able to borrow more. As a comparison, however, the majority of findings detect a **negative** relation between profitability and debt leverage (Titman and Wessels (1988), Rajan and Zingales (1995), Baker and Wurgler (2002), Fama and French (2002)). In line with the pecking-order theory, a recent paper by Faulkender and Petersen (2005) use sales instead of total assets as the divisor of the ratio variables and conjecture that profitable firms are reluctant to use debt unless their internal funds are exhausted due to asymmetric information costs, thus lower leverage is expected.

d. Uniqueness Titman, et al. (1988) and Faulkender, et al. (2005) find a significant **negative** relation between leverage and Research and development expenditure

(thereafter, $r\&d$) scaled by sales (uniqueness factor). They interpret the inverse relationship as: firms with more $r\&d$ suffer from higher financial distress and thus, will use less debt. This interpretation is in line with the trade-off theory. However, Shyam-Sunder and Myers (1999) use variables in levels instead of ratios in a regression model, and find $r\&d$ is **positively** related to leverage. They conclude that increasing $r\&d$ will enlarge a firm's financing deficit, and hence, financial deficit is **positively** correlated with leverage according to pecking order theory.

e. Growth The empirical literature shows a mixed pattern of the market-to-book ratio (growth factor), with most studies finding the market-to-book ratio negatively relates to leverage (Rajan and Zingales (1995), Baker and Wurgler (2002), Goyal, et al. (2002), Faulkender and Petersen (2005)). Myers (1977) suggests a high market-to-book ratio is associated with higher future growth opportunities. Based on pecking order theory, equity funding is more costly than debt due to information asymmetry. Therefore, high growth firms may be reluctant to issue equity even when they have to pass up optimal investment opportunities, and thus, high leverages are expected.

The above gives a summary of contradictory conclusions on the relationship between leverage and firm characteristics; these contradictions occur even when there are commonalities in the variables and research method. In Chapter 2, we argue the spurious ratio problem documented by Barraclough (2007) helps to explain why conflicting results have previously been observed. We found the confidence intervals generated by the simulation method have much wider ranges than those under conventional lev-

els. Therefore, ratio variables are shown to be significantly positive or negative under standard statistical inferences but they are actually insignificant. Specifically, their corresponding t-values are located within the boundary gap between the standard statistical interval and the simulated interval. To be comparative, the same variables are used in our probit model.

3.2.2 Probit/Logit models in capital structure studies

In contrast to linear multiple regression models, binary response models (probit or logit) consider the possible non-linear relationship between the debt issuance decision and its determinants. The choice between a probit model and logit model is not essential as they both use the Maximum Likelihood Estimation (MLE) method and estimation results are similar⁴. We adopt the probit model which takes the form:

$$\begin{aligned}
 P[Y = 1|X] &= \Phi(X'\beta) \\
 Y^* &= X'\beta + \epsilon \\
 Y &= \begin{cases} 1 & , \text{ if } Y^* > 0 \\ 0 & , \text{ Otherwise} \end{cases}
 \end{aligned}$$

Where P is probability, and Φ is the probit link function—the cdf of the standard normal distribution. It is also possible to motivate the probit model as a latent variable model.

⁴The main difference between these two models is the distribution assumption on residuals; a Logit model assumes a logistic distribution while a normal distribution is used in a Probit model.

A number of studies model the debt versus equity choice using probit or logit methods (Marsh (1982), Bayless and Chaplinsky (1990), and Jung, et al. (1996)). Marsh (1982) uses both logit and probit models in the UK market and finds a negative effect of size to the likelihood of equity issue; Marsh's results also suggest the existence of optimal capital structure. In the debt-equity choice tests, when current debt ratio is lower than its target ratio, debt is issued and the dependent dichotomous variable is equal to 1; when the opposite occurs, equity is issued and accordingly, the dependent dichotomous variable is set at 0. The latent variable Y^* is not restricted in definition. For example, in Marsh (1982), Y^* is the difference between a firm's current and target financial leverage. Since target financial leverage is unobservable, he uses historical averages as target ratios. In contrast, our dependent variable simply indicates whether the debt is actually issued or not in the probit model. The benefits of doing so can be two-fold: firstly, the long-term debt is not assumed to be a substitute of equity. In practice, the choice of securities can be open, such as convertible bonds, short-term debt, dual issue, etc. Secondly, we avoid assuming the existence of target capital structure as Modigliani and Miller (1958) suggests no target capital structure.

Hovakimian, Opler and Titman (2001) use a logit model to investigate the choice between straight debt and equity. In contrast to previous studies, they test both the security issuance and retirement (i.e. repurchase). When a firm has cash surplus with a target capital structure in mind, the management chooses between retiring debt and repurchasing shares. No matter which they choose, the retirement affects financial leverage since its effect should be opposite to that of the security issuance choice. They find more profitable firms tend to issue debt rather than equity and

repurchase equity rather than retire debt. Similarly, Dittmar and Thakor (2007) use a logit model to test the manager's choice between equity and debt. They predict that a manager's decision depends on investor's sentiments about payoffs of the projects. Larger, more profitable firms are more likely to obtain funds from debt markets as investors in debt markets prefer to lend money to less risky firms. Our results suggest larger, more profitable firms issue debt, that are consistent with the results of Dittmar and Thakor (2007). In addition, we show firms with high r&d are less likely to issue debt which can be interpreted as these firms tend to be riskier in terms of bankruptcy risk. Baxter and Cragg (1970) find companies with high market-to-book ratios prefer equity issues. Martin and Scott (1975) show that low profitability and high tangibility are associated with more debt issuances. However, our results do not support the above two arguments.

Hovakimian, et al. (2004) focus on the case of dual debt and equity issues which are normally excluded from the sample in other studies. As they suggest dual issuing firms can achieve a target capital structure at relatively lower cost compared to single issuing firms. They separate the cases into three scenarios: debt issue vs. dual issue; dual issue vs. equity issue; and debt issue vs. equity issue. In the debt issue vs. equity issue case, they find a **positive** profitability & size effect and negative r&d expenses effect which all coincide with our results. Further, they find the probability of debt issue is associated with negative growth (market-to-book ratio) and tangibility, whilst our results do not support such relation.

3.3 Data

3.3.1 Sample composition

Some studies include both public straight and convertible long-term debt resulting in larger sample sizes than the sample of public straight debt issuances only. However, earlier survey studies suggest that issuers generally regard convertible debt as a delayed equity offering (e.g. Pilcher (1955), Brigham (1966), and Hoffmeister (1977)). Therefore, it is inappropriate to include convertible debt in the sample. In addition, several studies include both public and private long-term debt, however, the offering dates are not publicly ascertained for private debts which weakens data reliability. Further, a number of studies focus on debt maturity by considering short and long-term debts as substitutes, contrary to previous studies which examine the substitution effects between equity and debt.

This thesis focuses on leverage increases that are caused by public straight long-term debt issuances. In doing this, our research purpose is better defined, even though the sample size is smaller. The sample inclusion is in line with our initiative to compare our results to those of equity-debt substitutes studies, while at the same time the problems in the sample selection can be avoided.

A number of data selection criteria are imposed. First, we only include issuers of publicly issued straight debts with maturity of more than one year from the SDC platform during the sample period of 1986-2006. Issuances without announcement information are excluded. Second, firms without financial information on the Compustat

or price information on the CRSP are excluded. Third, firms in a regulated utility or a financial sector with the SIC codes of 4900-4999 and 6000-6999 are excluded since these firms are very different from their industry counterparts in terms of both assets structure and funding sources. Fourth, firms with missing information on total assets, sales, share outstanding and share price for the fiscal year-end prior to the debt offerings are deleted. Fifth, to eliminate the possible impacts of other events within the firms, issuers with any of the following events occurring 30 calendar days before and after the announcement dates of debt offerings are excluded: ordinary share issue, convertible bond issue, stock split, share repurchase, and merger & acquisition. Sixth, companies issuing straight long-term debt more than once during the same fiscal year are excluded. This exclusion is because; with two consecutive debt announcements occurring in the same financial year it is difficult to isolate the joint effect of these events. After imposing all the selection criteria, the final sample consists of 719 debt issue observations from 454 firms. The financial data required to measure our firm variables are obtained from the year-end financial statements prior to offerings as it is reasonable to assume that managers make their financing decisions based on the prior year's financial results.

[Table 3.1 about here]

Industry and size are used as matching dimensions in our study. Table 3.1 reports the distribution and size descriptive summary of our sample of debt issuers in terms of industry. About 40% of the total issuances fall into five industry categories: Chemicals, Communication, Food, Oil, and Transportation equipment industries. In addition, these firms on average are sized over US\$3,000 millions in terms of total assets value.

[Table 3.2 about here]

Table 3.2 presents summary statistics on the variables, and these statistics are then compared with the estimations on all firms which are obtained from the Compustat without imposing our selection criteria (thereafter 'all Compustat sample'). The median of sales in our sample is US\$2,093 million, which is much higher than those of 'all Compustat sample'. This size difference suggests larger firms have relatively easier access to public debt markets, consistent with previous studies (Frank and Goyal (2008)). Similar patterns are also observed in other variables. For instance, the book leverage (market leverage) ratio is 56% (36%) in our sample and is 38% (24%) in the 'all Compustat sample', confirming the finding of Lemmon (2002) that financially unconstrained firms have higher debt capacities, thus they primarily use debt to meet their deficits while constrained (normally small, high-growth) firms issue more equity.

3.3.2 Sample and control firms selection

To employ the dichotomous probit model, a matching sample (i.e. non-issuers) is obtained using Barber and Lyon's (1996) matching firm approach where every observation is matched with a non-issuer for each year according to its industry and size. Barber and Lyon claim that the matching firm method yields better specified test statistics than the factor models. This approach is prevalent for event effects research purpose in corporate finance field (Kaplan (1989), Dann, Masulis, and Mayers (1991), DeGeorge and Zeckhauser (1993)). Industry match is defined as firms having the same first 2-digit SIC code and size matching is in terms of the book value of total assets.

Firms within the same industry are similar in their firm characteristics given that they all face the same market and industry condition, business operating risks, and asset risks, etc. Bowen, et al. (1982) and Bradley, et al. (1984) also suggest firms tend to retain their relative leverage ratio rankings within industry over time.

Similar to Barber and Lyon (1996) who use the range of [70%, 130%] for size matching, the size of our control firm has a range of [60%, 140%] for a given candidate firm. However, different to Barber and Lyon who employ a control firm that is the closest in size when finding a control firm within their size boundary is not possible, we exclude these firms because we believe the closest size matching (outside the size boundary) creates potential selection errors. For instance, such a way of matching may result in a control firm having a much smaller size and the control firm under this situation may not have the same ability to access debt markets, compared with the candidate firm. This procedure reduces our sample size from 987 to 719 observations.

Given two firms (a firm with debt issuance and its non-issuance matching firm) sharing analogous market conditions, assets structure, size, and business risks, along with the fact that both can access debt markets, it is interesting to explore why they make different debt issuance decisions. The way we select a matching firm is motivated by the attempts to investigate factors affecting a firm's capital structure after controlling for industry and size. The selection process is as follows:

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the SDC platform. Subsequently, all the above three databases are merged together by which result in 1224 debt issuances.

Step 3: Issuing firms and their corresponding non-issuers matches are obtained.

Step 4: The debt issuances with other ongoing events occur within the event window of $[-30, +30]$ are filtered out. There is no theoretical guidance on the choice of event window. However, wider windows provide better alleviation of the possible influence of other events. While, our sample size is greatly reduced if a wider event window is applied. Given the trade-off, a decision is made to favour the event window of $[-30, +30]$ which results in 987 issuances.

To match with a control firm in the same industry, the matching process mentioned above may have another problem. In some situations, for example, some firms may have several matches in a given year, while others may have a unique match, especially for the industries containing few public companies. To solve this problem, we first run the matching procedure mentioned above and obtain matching status for each sample firm for each year. Firms with only one match in a given year are highlighted (i.e. 156 cases). After that, the matching process is rerun with these firms granted a priority matching and then the remaining firms are subsequently matched. The procedure repeats 1,500 times to ensure the duplicated control firms are minimised. Finally, the dichotomous variable is created with value of 1 for our sample firms; and 0 for the control firms. Our final sample consists of 719 debt issuances from 454 issuing firms and 719 non-issuance matches.

3.4 Monte-Carlo simulation based statistical inference and the probit model results

We implement a probit model using the Maximum Likelihood Estimation method (MLE) to detect the determinants of long-term debt issuances. This method models a firm's financial choice of issuing debt or not. When debt is issued, the value of the dichotomous variable (dependent variable) is 1, otherwise 0, which represents the probability of debt issuance. The probability is then explained by a set of firm characteristics. The probit model is shown below:

Probit model:

$$\begin{aligned}
 \text{Dummy} &= \begin{cases} 1 & , \text{ Firms who issue debt} \\ 0 & , \text{ Control firms} \end{cases} \\
 P(Y = 1|X) &= \text{Probit}(b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r\&d_i}{s_i} + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + \epsilon_i)
 \end{aligned} \tag{3.1}$$

Where

– ta_i is the book value of total assets;

– ppe_i is the value of net property, plant and equipment;

– s_i represents net sales;

– $r\&d_i$ is research and development expenditures;

– $ebitda_i$ is operating income before depreciation;

– mva_i is market value of assets, calculated as the book value of total assets less the

book value of equity plus the market value of equity, and

$-\epsilon_i$ is the error term following a normal distribution; with the mean of 0 and uncorrelated to the X variables.

To detect the spurious ratio problem, we adopt the simulation technique developed by Barraclough (2007) with a modification that allows the simulation to be used in the probit model. In the procedure, Y is now a dummy variable and is drawn from a binomial distribution of which 719 observations are valued at 0, and 719 valued at 1. The Monte-Carlo simulation process is as follow:

Step 1: The values of X and Z variables are generated using the following formulas with the means, standard deviations, and cross correlations of X, Z variables are achieved from the actual sample and are then used as input in our simulation.

$$X_i = \mu_X + \gamma_i; \quad \text{and}$$

$$Z_i = \mu_Z + \xi_i$$

Where

$-\mu_X$ denotes the mean values of X variable including: ppe, r&d, ebitda and ta, mva (ta, mva are achieved from exponentiations of $\ln(\text{ta})$, $\ln(\text{mva})$);

$-\mu_Z$ presents the mean value of Z variable in natural logarithm form: $\ln(\text{ta})$, $\ln(s)$ and $\ln(\text{mva})$ and then exponentiated to obtain their levels.

$-\gamma_i, \xi_i$ are the error terms.

The null hypothesis assumes an arbitrary association between X and Z. In addition,

to integrate the sample characters into simulated data, the error terms for X and Z are drawn from a multiple normal distribution with a mean of 0, variance covariance matrix of V_{XZ} is obtained from the actual sample as follow:

$$V_{XZ} = \begin{vmatrix} \sigma_{ppe}^2 & & & & & \\ \sigma_{ppe,rnd} & \sigma_{rnd}^2 & & & & \\ \sigma_{ppe,ebitda} & \sigma_{rnd,ebitda} & \sigma_{ebitda}^2 & & & \\ \sigma_{ppe,\ln(s)} & \sigma_{rnd,\ln(s)} & \sigma_{ebitda,\ln(s)} & \sigma_{\ln(s)}^2 & & \\ \sigma_{ppe,\ln(ta)} & \sigma_{rnd,\ln(ta)} & \sigma_{ebitda,\ln(ta)} & \sigma_{\ln(s),\ln(ta)} & \sigma_{\ln(ta)}^2 & \\ \sigma_{ppe,\ln(mva)} & \sigma_{rnd,\ln(mva)} & \sigma_{ebitda,\ln(mva)} & \sigma_{\ln(s),\ln(mva)} & \sigma_{\ln(ta),\ln(mva)} & \sigma_{\ln(mva)}^2 \end{vmatrix}.$$

Note that the natural logarithm of Z ($\ln(Z)$) is first achieved from the actual sample and then exponentiated to obtain the simulated data in levels. The rationale is to avoid the simulation generating a negative value for **ta**, **mva** and **s**.

Step 2: 10, 000 simulation runs are performed for Models 3.1. The simulated results on White (1980) corrected t-values, intercepts, and adjusted R-squared values are recorded for each simulation run and ranked on their values.

Step 3: The critical values for the t-statistics are within the range of the 2.5 and 97.5 percentiles that correspond to tests of significance at the two-tail 5% probability levels. For the adjusted R-squared, the 95th percentile adjusted R-squared is reported as the 5% cut-off R-squared value. Any estimate value located within the boundary of critical t-statistics is regarded as insignificant from zero.

[Table 3.3 about here]

Panel A of Table 3.3 presents cut-off values for the probit model. First, the slope coefficient values are very close to zero compared with the results from the financial leverage models. In addition, the critical t-values are very close to conventional levels of $[-1.96, +1.96]$, which suggests that even when ratios are used in the probit model, conventional statistical inference is still valid. Hence, the spurious ratio problem documented by Barraclough (2007) is not evident in our probit model. Further, the critical McFadden's Pseudo R-squared value is achieved of 0.0058 at the 95 confidence level.

Panel B of Table 3.3 reports the probit model results using the actual sample. Since our simulation results suggest that conventional statistical inference is valid in probit models, thus it can be used free of the spurious regression problem. The results suggest size and profitability measures are positively correlated to the likelihood of long-term debt issuance decisions which implies larger, more profitable firms tend to use debt financing. The findings support the trade-off theory where larger firms prefer utilising debts for tax benefit maximization purposes. The size effect is also consistent with the empirical findings in Lemmon, et al. (2008) and Faulkender and Pertersen (2005), who find larger firms are more likely to access debt markets and issue 35% more debt than others.

The uniqueness measure (r&d/s) is shown to be negatively correlated to the probability of debt issuance. This finding is in line with previous findings where firms with high r&d tend to be technology intensive companies and thus account for more intangible assets (or less tangible assets). In addition, the pseudo R-squared (0.03) with using the actual sample is greater than the critical level (0.0058), which suggests Model 3.1

is significant at the equation level.

3.5 Conclusion

This chapter investigates the likelihood of long-term debt issuance by a probit model to overcome the spurious ratio problem evidenced in the traditional multivariate regression models. With modifications to the Monte-Carlo simulation technique of Barraclough (2007), the cut-off values for slope coefficients, t-statistics and MacFadden's Pseudo R-squares are generated for the probit model. Our simulation based cut-off values are no different to conventional levels which indicates no spurious ratio problem. It appears that the Monte-Carlo simulation method is a reliable method to verify parametric statistical inferences.

By modeling the decision of debt issuance using a dichotomous variable, our results suggest leverage increasing firms tend to be larger, more profitable and firms with high r&d expenditures tend to be less likely to use debt as a means of financing.

Table 3.1: Summary statistics of long-term debt issuances in terms of industry and size

<i>Industry Sector</i>	<i>Num. of issues</i>	<i>Mean of total assets</i>
Chemicals and allied products	70	6091.98
Communication	59	9037.87
Food and kindred products	58	5696.8
Oil and gas extraction	46	3158.14
Transportation equipment	46	7101.45
Business services	33	7137.77
General	31	918.73
Paper and allied products	31	4262.39
Industrial machinery and equipment	30	4336.61
Electronic&other electric equipment	26	7261.42
Food store	24	5037.9
Instruments and related products	23	3717.46
General merchandise stores	22	9483.77
Primary metal industries	19	2201.63
Petroleum and coal products	18	9917.46
Health services	15	1133.39
Amusement & recreation services	14	2507.8
Printing and publishing	13	2233.33
Wholesale trade-nondurable goods	13	3219.34
Fabricated metal products	11	1451.37
Transportation by air	10	9340.44
Whole sale trade-durable goods	10	1633.34
Others	97	2015.77
Total	719	4946.75

Note: all the values of "Mean of total assets" item are in million US dollars.

Table 3.2: Sample descriptive statistics

		Panel A: Variable composition	
Symbol	Name	Compustat data item	
1.s	Sales	SALE	
2.ppe	Property, plant & equipment	PPENT, if missing then use PPEGT	
3.mva	Market value of assets	AT-(AT-LT-PSTKL+TXDITC+DCVT)+CSHO*PRCC_F	
4.r&d	Research & Development expenditures	RDIP	
5.ebitda	Operating income before depreciation	OIBDP	
6.d	Total debts	AT-(AT-LT-PSTKL+TXDITC+DCVT)	
7.ta	Total assets	AT	

Panel B: Comparison of summary statistics for our sample firm-year and all Compustat firm-year (1985-2005)

		Our sample				All Compustat sample				(Million US\$)	
Variable		Mean	Median	Std Dev	Num. of obs	Variable	Mean	Median	Std Dev		Num. of obs
1.s		5287	2093	8614	719	1.s	1111	93	6117		94060
2.ppe		1859	722	3385	719	2.ppe	407	17	2484		94060
3.mva		9330	3183	19835	719	3.mva	2102	142	14611		94060
4.r&d		110	0	404	719	4.r&d	26	0	220		94060
5.ebitda		764	297	1277	719	5.ebitda	160	8	1026		94060
6.d		2930	1138	4907	719	6.d	751	34	7396		94060
7.ta		4947	2039	8577	719	7.ta	1234	90	9373		94060

Note: We require both samples have positive and no missing data on compustat AT (total asset), SALE (sales), PRCC_F (share price), CSHO (outstanding share numbers); Research & Development values are missing for about 2/3 of the samples; and we replace these missing values with 0.

Panel C: Cross-correlation of variables for cross-sectional sample

Variable	ppe	ln(s)	r&d	ebitda	ln(ta)	ln(mva)
ppe	1					
ln(s)	0.53	1				
r&d	0.29	0.34	1			
ebitda	0.8	0.63	0.62	1		
ln(ta)	0.63	0.9	0.37	0.69	1	
ln(mva)	0.58	0.88	0.41	0.71	0.96	1
d	0.74	0.61	0.59	0.85	0.69	0.66

Note: We use ln(S), ln(TA) and ln(MVA) instead of S, TA, MVA in the simulation to ensure these variable values are positive.

Table 3.3: Monte-Carlo simulation based inferences for the probit model and model results

Panel A:Simulation critical values for the probit regression model

$$Probit\left(Y=1|X\right)=b_0+b_1\frac{ppe}{ta_i}+b_2\ln(s_i)+b_3\frac{r\&d_i}{s_i}+b_4\frac{ebitd_i}{ta_i}+b_5\frac{mva}{ta_i}+\varepsilon_i$$

Prob.level	Intercept		ppe/ta		ln(s)		r&d/s		ebitda/ta		mva/ta		R-squared
Debt	b0	t(b0)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	b5	t(b5)	
2.50%	-0.3229	-1.93	-0.0069	-2.05	-0.0433	-2	-0.0393	-2.01	-0.01702	-2.04	-0.0017	-2.13	0.0058
97.50%	0.3279	1.96	0.0069	2.06	0.04278	1.98	0.0388	2.02	0.0174	2.04	0.0017	2.1	
Note: 1. replication runs=10,000 number of observations for each simulated dataset: n=719													

Panel B: Actual results from the probit model

Prob(Y=1)	Intercept		ppe/ta		ln(s)		r&d/s		ebitda/ta		mva/ta		R-squared
	b0	t(b0)	b1	t(b1)	b2	t(b2)	b3	t(b3)	b4	t(b4)	b5	t(b5)	
	-0.58***	-3.11	0.04	0.25	0.05**	2.00	-4.98***	-5.35	2.11***	3.92	-0.001	-0.03	0.028

Note: 2. In the last column the R-squared value is MacFadden's Pseudo R-squared value.
 3.d denotes the book value of total assets; ppe is the value of net property, plant and equipment; s is net sales; r&d is research & development expenditure; ebitda is operating income before tax; mva is market value of assets; v and ε are error terms.

Chapter 4

The Impact of Long-term Debt Issuances

4.1 Introduction and previous studies

Chapter 2 and 3 discussed the spurious ratio problem, as documented by Barraclough (2007), found in previous capital structure studies; and introduced a probit model to find the determinants of long-term debt issuance. This chapter extends this work and aims to determine whether the long-term debt issue decision affects a firm's ex post stock performance. The price impact of the long term debt issue decision is crucial at both the empirical and theoretical levels. However, the empirical results are unresolved as both zero and non-zero (negative and positive) effects are suggested in the literature. At the theoretical level, the announcement effect can be extended to a fundamental research question: How is asymmetric information reflected in asset pricing?

Chapter 4 provides evidence of how private information possessed by long-term debt issuers affects post stock performance. We find that, once private information (or self-selection) is considered, there is no substantial price impact of debt announcements. The zero price impact finding is consistent with Modigliani and Miller's (1958, hereafter MM) irrelevance theory. MM claim that debt or equity issues are simply different sources of funding; hence, the financial decisions on debt or equity will leave a firm's market value unchanged as it has no impact on the investment opportunities for issuing firms. Rather, it is investment opportunities which determine a firm's market value. Therefore, debt issue announcements have zero impact on a firm's stock performance.

However, Masulis (1980), Dann (1981), and Vermaelen (1981) find a firm's leverage-increasing changes bring new information to the market and investors react **positively** to debt issue announcements. On the other hand, Dann and Mikkelsen (1984) document a marginally **negative** return (-0.37%) during the two-day announcement period on debt issuances. Eckbo (1986) also finds that straight debt offerings have non-positive price effects on US industrial companies.

The debate between zero (Modigliani and Miller, 1958) and non-zero impacts (i.e., Eckbo (1986), Masulis (1980)) largely focuses on whether or not the issuance decision conveys new information to the market that alters investors' expectation of a firm's investment policy. In addition, studies showing non-zero impacts: both negative and positive, assume that an unanticipated issuance will cause firm revaluation. Even though both directions of non-zero impacts rely on information asymmetry frameworks, Ross (1977) and Heinkel (1982) suggest that management possesses superior private

information concerning the intrinsic value of the firm. An unanticipated increase in debt leverage signals that the management is optimistic of a firm's earning prospects with which the new debt is repaid in the future. Therefore, a positive price impact is expected. In contrast, Miller and Rock (1985) predict a negative price impact of debt issue announcements using a theoretical asymmetric information model. Given the assumption that management and investors both have full information about a firm's investment opportunities, external financing is then unanticipated by investors as this is against their belief that internal earnings should be able to cover future investment needs. Therefore, both debt and equity decisions are regarded as bad news as any unanticipated external financing indicates that expected earnings were higher than actual earnings¹. In addition, Miller and Rock (1985) suggest that more pronounced negative than average abnormal returns will accompany larger unanticipated proceeds.

To determine the price impact of long-term debt issuances, we first adopt an event study to investigate announcement effects. We use Barber and Lyon's (1996) matching firm approach with matching dimensions of industry and size. We follow with a parametric t-test to find whether the cumulative abnormal returns are different from zero with a sample of US public straight debt announcements from 1986 to 2006. The result suggests a *negative* price impact which seems to support both Miller and Rock's (1985) prediction and the empirical results from Dann and Mikkelsen (1984), Eckbo (1986).

However, price effects for firms issuing debt may be different from non-issuance

¹In contrast, dividends are viewed as negative financing which means the expected earnings had been lower than actual earnings.

firms. The issuance decision made by management is not random but related to information unobservable by the public. As a consequence, if these unobservable factors are not included, the OLS estimators are then biased due to a self-selection problem. From the econometric point of view, Heckman (1979) views the self-selection factor as an omitted variable which can be corrected by his two-step model.

Li and Prabhala (2005) interpret the self-selection factor as private information possessed by management and suggest that Heckman's two-step model can also be used to test private information effects. If the slope coefficient of the self-selection factor (also known as 'Heckman's lambda' or 'the Inverse Mills' ratio') is statistically significantly different from zero, then private information is suggested. In other words, if the private information has non zero value, the value will be carried to the firm's ex post stock performance.

We follow Heckman (1979) and use a probit model in the first stage to specify self-selection effects measured by Heckman's lambda. The second stage tests the hypothesis of price impacts by building a regression model between the cumulative abnormal returns (CAR) and Heckman's lambda. Our result suggests the negative price impact, when the CAR is tested alone, disappears once self-selection is considered. Then, in parallel with Chapter 2 and 3, more potential determinants examined in the literature are included using the same OLS method repeated for the second step. Further, we use a range of different specifications including a number of different benchmarks used in calculating CARs, and find that the zero price impact result is robust.

The remainder of this chapter is organized as follows. Section 4.2 discusses data

collection, matching firm procedures, and summary statistics on long-term debt issuers. Section 4.3 uses Heckman's two-step model to detect significance of abnormal returns followed by robustness tests using a range of different specifications in Section 4.4.

4.2 Data

4.2.1 Sample composition

Sample components vary in the literature; some researchers include both public straight and convertible long-term debt resulting in a large sample size. However, earlier survey studies suggest that issuers generally regard convertible debt as a delayed equity offering (e.g. Pilcher (1955), Brigham (1966), and Hoffmeister (1977)). Therefore, it is inappropriate to include convertible debt in the sample. In addition, several studies include both public and private long-term debt, however, the offering dates are not publicly ascertained for private debt which weakens data reliability. Further, a number of studies focus on debt maturity by considering short and long-term debt as substitutes. This is contrary to previous studies which examine substitution effects between equity and debt.

This thesis focuses on leverage increases caused by public straight long-term debt issuances. In doing so, our research purpose is better defined, even though the sample size is smaller. The sample inclusion is in line with our initiative to compare our results to those of equity-debt substitution studies, while at the same time problems in sample selection can be avoided.

A number of data selection criteria are imposed. First, we only include issuers of publicly issued straight debts with maturity of more than one year from the SDC platform during the sample period of 1986-2006. Those issues without announcement information are excluded. Second, firms without financial information on the Compustat or price information on the CRSP are excluded. Third, firms in a regulated utility or a financial sector with the SIC codes of 4900-4999 and 6000-6999 are excluded since these firms are very different from their industry counterparts in terms of both assets structure and funding sources. Fourth, firms with missing information on total assets, sales, shares outstanding and share price for the fiscal year-end prior to the debt offerings are deleted. Fifth, to eliminate the possible impacts of other events within the firms, issuers with any of the following events occurring 30 calendar days before and after the announcement dates of debt offerings are excluded: ordinary share issue, convertible bond issue, stock split, share repurchase, and merger & acquisition. Sixth, companies issuing straight long-term debt more than once during the same fiscal year are excluded. This exclusion is because; with two consecutive debt announcements occurring in the same financial year it is difficult to isolate the joint effect of these events. After imposing all the selection criteria, the final sample consists of 719 debt issue observations from 454 firms during the 21 years. The financial data required to measure our firm variables are obtained from the year-end financial statements prior to offerings as it is reasonable to assume that managers make their financing decisions based on the prior year's financial results.

[Table 4.1 about here]

Industry and size are used as matching dimensions in our study. Table 4.1 reports the

distribution and size descriptive summary of the long-term debt issuances sample in terms of industry. About 40% of the total issuances falls into five industry categories: Chemicals, Communication, Food, Oil, and Transportation equipment industries. In addition, the issuing firms on average are sized over US\$3,000 millions in terms of total assets value.

[Table 4.2 about here]

Table 4.2 presents summary statistics on all the variables used and these statistics are then compared with the estimations on all firms which are obtained from the Compustat without imposing our selection criteria (thereafter "all Compustat sample"). The median of sales in our sample is US\$2,093 million, which is much higher than those of 'all Compustat sample'. This size difference suggests larger firms have relatively easier access to public debt markets, consistent with previous studies (Frank and Goyal (2008)). Similar patterns are also observed in other variables. For instance, the book leverage (market leverage) ratio is 56% (36%) in our sample and is 38% (24%) in the 'all Compustat sample', confirming the finding of Lemmon (2002) that financially unconstrained firms have higher debt capacities, thus they primarily use debt to meet their deficits while constrained (small, high-growth) firms issue more equity.

4.2.2 Sample and control firms selection

To employ the dichotomous probit model, a matching sample (i.e. non-issuers) is obtained using Barber and Lyon's (1996) matching firm approach where every observation is matched with a non-issuer for each year according to its industry and size. Barber

and Lyon claim that the matching firm method yields better specified test statistics than the factor models. This approach is widely used in corporate finance (Kaplan (1989), Dann, Masulis, and Mayers (1991), DeGeorge and Zeckhauser (1993)). Industry match is defined as firms having the same first 2-digit SIC code and size match is in terms of the book value of total assets.

Firms within the same industry are similar in their firm characteristics given that they all face the same market and industry condition, business operating risks, and asset risks etc. Bowen, et al. (1982) and Bradley, et al. (1984) also suggest firms tend to retain their relative leverage ratio rankings within industry over time.

Similar to Barber and Lyon (1996) who use the range of [70%, 130%] for size matching, the size of our control firm has a range of [60%, 140%] for a given candidate firm. However, in contrast to Barber and Lyon who employ a control firm that is the closest in size when finding a control firm within their size boundary is not possible, we exclude these firms because we believe the closest size matching (outside the size boundary) creates potential selection errors. For instance, such a way of matching may result in a control firm having a much smaller size and the control firm under this situation may not have the same ability to access debt markets, compared with the candidate firm. This procedure reduces our sample size from 987 to 719 observations.

Given two firms (a firm with debt issuance and its non-issuance matching firm) sharing analogous market conditions, assets structure, size, and business risks along with the fact that both can access debt markets, it is interesting to explore why they make different debt issuance decision. The way we select matching firms is motivated by

the attempts to investigate factors affecting a firm's capital structure after controlling for industry and size. The selection process is as follows:

Step 1: We first merge the Compustat database with the CRSP database to ensure a smooth transition between financial and return data.

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To match with a control firm in the same industry, the matching process mentioned above may have another problem. In some situations, for example, some firms may have several matches in a given year, while others may have only a unique match, especially for an industry containing few public companies. To solve this problem, we first run the matching procedure mentioned above and obtain matching status for each sample firm each year. Firms with only one match in a given year are highlighted (i.e. 156 cases). After that, the matching process is rerun with these firms granted a priority matching and then the remaining firms are matched subsequently. The procedure repeats 1,500 times to ensure the duplicated control firms are minimised. Finally, the dichotomous

variable is created with a value of 1 allocated to our sample firms; and 0 for the control firms. Our final sample consists of 719 debt issues from 454 issuing firms and 719 non-issuance matches.

4.3 Methodology and Results

4.3.1 Significance testing for abnormal returns alone

Hypothesis:

$H_0 : t_{CAR} = 0$ There are **no** significant abnormal returns;

$H_1 : t_{CAR} \neq 0$ Abnormal returns are significantly different from zero.

$$t_{CAR} = \frac{\overline{CAR}}{\sigma(CAR_{it})/\sqrt{n}} \quad (4.1)$$

[Table 4.3 about here]

We apply a t-test to examine the significance of the cumulative abnormal returns (CAR) to find whether it is significantly different from zero. This implies if the null hypothesis is accepted, then we cannot reject the zero price impact statistically. To employ the above test, first, an event window needs to be specified to capture the announcement effect. Empirically, the abnormal returns at corresponding event dates are found to be insignificant due to information leakage. Thus, longer event windows are considered by adding up the abnormal returns during the observation window periods. In practice, not only days after the events, but also days prior to events are

examined; also various lengths of event windows are attempted as investor may react at a different rate to announcements. We use the matching firm approach of Barber and Lyon (1996), and abnormal returns are calculated as the cumulative return on the sample firm less the return on its corresponding control firm during the observing windows. The first panel in Table 4.3 reports the average cumulative abnormal return at the window of $[-30,+30]$ trading days is found to be *negatively* significant with a t-value of -2.09. This suggests shareholders see long-term issuances as bad news and a post underperformance is exhibited. Our finding is consistent with Miller and Rock (1985), Dann and Mikkelson (1984), and Eckbo (1986).

A number of previous studies indicate that market reactions to capital structure changes occur almost entirely within a two-day period (e.g. Masulis (1980), Dann (1981), Vernaek (1981), Mikkelson (1981), Dann and Mikkelson (1984), Asquith and Mullins (1986), and Masulis and Korwar (1986)). In contrast, we don't find the two-day effect; the abnormal returns are only significant at the window of $[-30,+30]$ which suggests a slower rate of reaction to debt announcements².

4.3.2 Heckman's two-step model

We use Heckman's (1979) two-step self-selection model to investigate the price impact of long-term debt issuances. A probit model is implemented to control for latent sample

²In total, we have tried ten different event windows and use the 5% confidence level, the type I error can be substantially higher than only testing one window. Therefore, we apply the Bonferroni correction by adjusting the p-value divided by the number of outcomes being tested. E.g. at the 5% level and assuming 5 event windows, the Bonferroni correction would use the $0.05/5 = 0.01$ level. At the 0.01 confidence level, the cutoff t-value would be 2.576 (the 1% level) instead of 1.96 (the 5% level).

self-selection bias. It can be argued that firms self-select themselves by issuing debt, while the self-selection factor is unobservable and Heckman treats the self-selection factor as an omitted variable. With the Maximum Likelihood Estimation method employed in the probit model, the omitted variable (also known as 'Heckman's lambda', or 'Inverse Mills' ratio') is then added as another explanatory variable along with other presumed determinants to explain stock performances in the second step. Without the specification step, the OLS estimators maybe biased in the second step.

The first step: Selection specification

$$Dummy = \begin{cases} 1 & , \text{ Firms who issue debt} \\ 0 & , \text{ Control firms} \end{cases}$$

$$P(Y = 1|X) = Probit(b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r\&d_i}{s_i} + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + b_6 mtr_i + \epsilon_i)$$

Where a dichotomous dependent variable is used to distinguish issuing firms with dummy value 1 and control firms valued at 0. In line with Chapter 2 and 3, asset structure (ppe/ta), size ($\ln(s)$), profitability ($ebitda/ta$), uniqueness ($r\&d/s$), growth (mva/ta) are chosen as firm characteristics proxies³. In addition, we use the marginal tax rate (mtr) variable developed by Graham (1996) to measure a firm's tax benefits of issuing debt. Tax effect is crucial to test capital structure theories, for example, the trade-off theory sees capital structure the consequence of rebalance between a firm's tax benefits and bankruptcy costs.

³These variables are ranked as either Tier-1 or Tier-2 robust firm characteristic factors according to Frank and Goyal (2003).

The second step: A regression model to test the price impact after controlling for self-selection

$$CAR_i = \alpha + \beta\lambda_i + \varepsilon_i \quad (4.2)$$

Where

– CAR_i denotes the cumulative abnormal return;

– λ_i is the inverse Mills' ratio which is achieved from the specification stage;

– α is constant;

– β denotes the slope coefficient of λ .

– ε_i is the error term with mean 0 and iid.

With the above model, we can test the price impact after controlling for sample selection bias.

Hypothesis:

$H_0 : \alpha = 0$ There are **no** significant abnormal returns after controlling for self-selection.

$H_1 : \alpha \neq 0$ Abnormal return is significantly different from zero.

Note, here we test the price impact after controlling for self-selection bias by including Heckman's lambda which is different to testing the significance of abnormal returns alone (Section 4.3.1). If the intercept term (α) is significantly different from 0, then the insignificant result suggests the unobserved self-selection factor is not enough to explain the price impact. In contrast, if the intercept is insignificant then it suggests there is no significant abnormal returns once self-selection is considered.

4.3.3 Results

[Table 4.4 about here]

Panel A of Table 4.4 reports results of the probit model—the first step of Heckman (1978). Results suggest that uniqueness ($r\&d/s$) is negatively associated to the probability of debt issuance; profitability measure and marginal tax rate in contrast have positive relationship to debt issuance likelihood. Panel B of Table 4.4 shows the intercept term (α) is insignificant in Model 4.2, which suggests once self-selection is controlled for there are no abnormal returns from long-term debt issuance. The model is significant at the equation level with a p-value of 0.054; the self-selection control (λ) is statistically significant using a 90% confidence level. This finding is then consistent with Modigliani and Miller's (1958) irrelevance prediction of capital structure decisions.

According to Li and Prabhala (2005), the self-selection factor can also be interpreted as a measure of private information; the sign of λ suggests private information possessed by issuers affects firms' performance positively (if '+') or negatively ('-'). This result supports the information asymmetry explanation of Miller and Rock (1985). They show, given the assumption that management and investors both can access full information about a firm's investment opportunities; the external financing announcement is bad news to the market. The negative sign of λ , in terms of private information affecting managers' debt issuance decisions, appears to be bad news for investors.

4.3.4 Full-model including the determinant factors

To be in line with Chapter 3 and the literature, more factors are added as explanatory variables in Equation 4.2 to test more dimensions of capital structure theories. In addition to the six firm characteristic measures from the specification step, the 10-year government bonds interest rate which is 91 days prior to the announcement date is used to examine whether market timing effects exist⁴. Baker, et al. (2003) find evidence of market timing in long-term debt markets. Miller and Rock (1985) predict the deeper negative average abnormal returns are accompanied by larger unanticipated proceeds size. Therefore, the proceeds variable ($\text{proceeds}/ta$) is included to test Miller and Rock's model. Li and Prabhala (2005) also recommend using proceeds as proceeds volume is not disclosed to the public until the announcement date. The proceeds size information is viewed as private information of management before it is released. Last, the inverse Mills' ratio from the specification step is included to control for sample selection bias; and private information in the sense of Li and Prabhala (2005).

$$CAR_i = b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r\&d_i}{s_i} + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + b_6 Bondrate_i + b_7 \frac{proceeds_i}{ta_i} + b_8 \lambda_i + v_i \quad (4.3)$$

⁴We assume if there are market timing effects in debt markets, issuers may use the long-term bond interest rates one quarter prior to issue as a benchmark.

In addition, to make the results of Equation 4.3 more comparable, an OLS model without controlling for self-selection is also tested in Equation 4.4.

$$\begin{aligned}
 CAR_i = & b_0 + b_1 \frac{ppe_i}{ta_i} + b_2 \ln(s_i) + b_3 \frac{r\&d_i}{s_i} \\
 & + b_4 \frac{ebitda_i}{ta_i} + b_5 \frac{mva_i}{ta_i} + b_6 Bondrate_i + b_7 \frac{proceeds_i}{ta_i} + v_i
 \end{aligned} \tag{4.4}$$

4.3.5 Results

The estimation results of Equation 4.3 and 4.4 are shown in Panel B of Table 4.4. The constant term is insignificant from zero, which again suggests no price impact of debt issuances. The model is insignificant at the equation level with a p-value of 0.191 and R-squared of 0.005. The proceeds ratio has a marginal *negative* association which supports Miller and Rock's (1985) prediction on the relationship between proceeds size's adverse impact to abnormal returns. Noticeable, the lambda is insignificant which indicates once other variables are included, no private information effect is evident and the negative stock performance once again disappears. This finding destabilizes the *negative* price impact proposition, however, supports the zero price impact hypotheses.

We compare the results of the estimation of Equation 4.4 to those of Equation 4.3. The results are similar for models with/without the self-selection measure given other proxies are equal. The intercept term is insignificant in models without Heckman's lambda. This is once again an evidence of the zero impact. Also, the model is insignificant at the equation level which is similar to the model including Heckman's lambda. When these two full models (Equation 4.3 and 4.4) are compared to Equation 4.2,

no private information effect is found when more potential determinants are included. Two possible reasons may account for the difference: first, once we add up more explanatory variables, some of them may embody the private information which overlaps with the self-selection measure (Heckman's λ). For example, Li and Prabhala (2005) suggest the proceeds size can be viewed as private information possessed by firms. Once factors like proceeds are included, the other private information measure (Heckman's λ) is not significant. Second, as the model is insignificant at the equation level, this may suggest other variables apart from Heckman's λ have no power to explain the price impact and thus should be dropped.

4.4 Robustness Testing

In the main test (Equation 4.2), we examine the private information effect by building a regression model between Heckman's λ and CAR. However, to assure these results are robust, we design three robustness tests as follows.

4.4.1 Robustness test 1: White's (1980) method for standard error corrections

[Table 4.5 about here]

In the first robustness test, in parallel to the matching firm approach used in our main test, we imply White's (1980) robustness correction to Equation 4.2 and 4.3. Panel A of Table 4.5 indicates a zero price impact based on the insignificant intercept term (α).

However, after correcting for standard errors, the results of Equation 4.4 change to be significant at the equation level and the proceeds ratio is still *negatively* significant. Noticeable, in both the main tests and robustness tests, debt maturity is insignificant which can be interpreted to imply no market timing effects. Although debt maturity is similar to the proceeds ratio proxying for private information possessed by issuers, the proceeds ratio appears to be more influential than debt maturity.

4.4.2 Robustness test 2: the (0,1) market model as benchmark

An alternative method to measure the abnormal returns is to calculate the cumulative returns from a sample firm minus its expected return using the CAPM model (Equation 4.5). However, prior to debt issuances, the sample firms may perform abnormally and the beta which is used to measure a firm's systematic risk thus may also deviate from its usual level. Consequently, the abnormal betas can result in biased abnormal returns. To alleviate this, we adopt the (0,1) market model (Equation 4.6) using the CRSP value-weighted index as the market portfolio (e.g. Eckbo (1986)).

$$AR_i = R_i - (\alpha_i + \beta_i R_m) \quad (4.5)$$

When we use the (0,1) market model, it takes the form of:

$$AR_i = R_i - R_m \quad (4.6)$$

We focus on the short-term impact of debt announcements rather than long-term, as the CARs in the long run suffer much more from measurement bias, new listing bias, and skewness bias (Barber and Lyon, 1996).

The third panel of Table 4.3 shows abnormal returns are significant at the windows spanning from $[-5, +5]$ to $[-40, +40]$ all with *positive* signs. This differs from the *negative* abnormal returns (before controlling for self-selection) using the matching firm approach. Whilst the second panel of Table 4.3 finds that using the CRSP equally weighted market index, the abnormal returns are insignificant at all windows. The findings suggest the price impact is sensitive to the benchmark being chosen which may explain the conflicting empirical results discussed earlier. Panel B of Table 4.5 indicates no variables are significant to explain the positive price impact of using the CRSP value weighted market index at both models with robustness correction (Equation 4.3 and 4.4). Noticeable, again the intercept term is found to be insignificant after controlling for self-selection; using the (0,1) market model also indicating no significant price impact, which is consistent with our main result.

4.4.3 Robustness test 3: the multi-issue firms as subsample

There are 168 firms accounting for 433 debt issuances during the observation period of 1986-2006, these firms then enter into the multi-issue subsample for the last robustness testing. It helps to find whether investors respond differently to firms visiting debt markets with higher frequency. For the multi-issue firms, a dummy variable is used to distinguish them from single issue firms. In addition, interaction terms are added for

all the X variables in Equations 4.3 and 4.4.

[Table 4.6 about here]

Panel B of Table 4.6 verifies our prediction that the intercept term is insignificant, thus once again confirming the zero price impact. If the results are compared to our main results, we find first, once the dummy for multi-issue firms and interaction items are included, size and profitability effects disappear; second, both of the marginal tax rate (+) and the research & development ratio (-) are still significant to the likelihood of debt issuance at the specification stage. In addition, the interaction term of multi-issue dummy and profitability shows marginally positively correlated to CAR. It suggests that increasing profitability is accompanied by a higher probability of debt issuance only for multi-issue firms but not single-issue firms.

4.5 Conclusion

This chapter examines the price impact of straight long-term debt issuances using Heckman's (1979) two-step approach in US markets from 1986 to 2006. The matching firm method developed by Barber and Lyon (1996) is adopted to calculate abnormal returns with matching dimensions of industry and size. A significant negative price impact of debt announcements at the event window of $[-30,+30]$ is evidenced. This finding supports the prediction of Miller and Rock (1986) that investors see debt issuance as bad news. However, we show that once self-selection is controlled for, the negative price impact disappears in both of our main tests and robustness tests. In addition, we find the price impacts rely on the benchmark chosen; for example, a zero

Table 4.1: Summary statistics of long-term debt issuances in terms of industry and size

<i>Industry Sector</i>	<i>Num. of issues</i>	<i>Mean of total assets</i>
Chemicals and allied products	70	6091.98
Communication	59	9037.87
Food and kindred products	58	5696.8
Oil and gas extraction	46	3158.14
Transportation equipment	46	7101.45
Business services	33	7137.77
General	31	918.73
Paper and allied products	31	4262.39
Industrial machinery and equipment	30	4336.61
Electronic&other electric equipment	26	7261.42
Food store	24	5037.9
Instruments and related products	23	3717.46
General merchandise stores	22	9483.77
Primary metal industries	19	2201.63
Petroleum and coal products	18	9917.46
Health services	15	1133.39
Amusement & recreation services	14	2507.8
Printing and publishing	13	2233.33
Wholesale trade-nondurable goods	13	3219.34
Fabricated metal products	11	1451.37
Transportation by air	10	9340.44
Whole sale trade-durable goods	10	1633.34
Others	97	2015.77
Total	719	4946.75

Note: All the values of "Mean of total assets" item are in million US dollars.

Table 4.2 Sample descriptive statistics

Panel A: Variable composition		
Symbol	Name	Compustat data item
1.s	Sales	SALE
2.ppe	Propert,plant &equipment	PPENT, if missing then use PPEGT
3.mva	Market value of assets	AT-(AT-LT-PSTKL+TXDITC+DCVT)+CSHO*PRCC_F
4.r&d	Research & Development expenditures	RDIP
5.ebitda	Operating income before depreciation	OIBDP
6.d	Total debits	AT-(AT-LT-PSTKL+TXDITC+DCVT)
7.ta	Total assets	AT

Panel B: Comparison of summary statistics for our sample firm-year and all Compustat firm-year (1985-2005)

Our sample		(Million US\$)		All Compustat sample				(Million US\$)	
Variable	Mean	Median	Std Dev	Num. of obs	Variable	Mean	Median	Std Dev	Num. of obs
1.s	5287	2093	8614	719	1.s	1111	93	6117	94060
2.ppe	1859	722	3385	719	2.ppe	407	17	2484	94060
3.mva	9330	3183	19835	719	3.mva	2102	142	14611	94060
4.r&d	110	0	404	719	4.r&d	26	0	220	94060
5.ebitda	764	297	1277	719	5.ebitda	160	8	1026	94060
6.d	2930	1138	4907	719	6.d	751	34	7396	94060
7.ta	4947	2039	8577	719	7.ta	1234	90	9373	94060

Note: We require both samples have positive and no missing data on compustat AT (total asset), SALE (sales), PRCC_F(share price), CSHO (outstanding share numbers); Research &Development values are missing for about 2/3 of the samples; and we replace these missing values with 0.

Panel C: Cross-correlation of variables for cross-sectional sample

Variable	ppe	ln(s)	r&d	ebitda	ln(ta)	ln(mva)
ppe	1					
ln(s)	0.53	1				
r&d	0.29	0.34	1			
ebitda	0.8	0.63	0.62	1		
ln(ta)	0.63	0.9	0.37	0.69	1	
ln(mva)	0.58	0.88	0.41	0.71	0.96	1
d	0.74	0.61	0.59	0.85	0.69	0.66

Note: We use the ln(S), ln(TA) and ln(MVA) instead of S, TA, MVA in simulation to ensure these variable values are positive.

Table 4.3: CAR t-statistics results using a range of benchmarks

INDEX	Event Window	T-value	P-value
Control group	[-40,+40]	-1.54	0.1233
	[-30,+30]	-2.09	0.0367
	[-20,+20]	-1.14	0.2562
	[-15,+15]	-0.56	0.5744
	[-10,+10]	-0.68	0.4958
	[-5,+5]	-0.3	0.7662
	[-3,+3]	0.22	0.8227
	[-2,+2]	-0.05	0.9639
	[-1,+1]	0.55	0.5805
	[-0,+0]	0.27	0.7844
CRSP equally weighted	[-40,+40]	1.09	0.2745
	[-30,+30]	0.61	0.5391
	[-20,+20]	0.47	0.6406
	[-15,+15]	0.35	0.7241
	[-10,+10]	0.35	0.7286
	[-5,+5]	0.37	0.7087
	[-3,+3]	0.36	0.7185
	[-2,+2]	-0.02	0.9847
	[-1,+1]	-0.3	0.7643
	[-0,+0]	-0.09	0.9312
CRSP value weighted	[-40,+40]	6.59	0
	[-30,+30]	5.48	0
	[-20,+20]	4.52	0
	[-15,+15]	3.9	0
	[-10,+10]	3.26	0.0011
	[-5,+5]	2.34	0.0191
	[-3,+3]	1.74	0.082
	[-2,+2]	1.19	0.2356
	[-1,+1]	0.87	0.3859
	[-0,+0]	1.06	0.2913

Table 4.4: Price impacts of long-term debt issuances: Heckman's (1979) two-step approach

$$Probit(Y=1|X)=b_0+b_1\frac{ppe}{ta_i}+b_2\ln(s_i)+b_3\frac{r\&d_i}{s_i}+b_4\frac{ebitda}{ta_i}+b_5\frac{mvq}{ta_i}+b_6mtr_i+\varepsilon_i$$

Panel A: Estimation for the first step using the probit model

N=1438 Chi2=68.6 P-value=0					
Intercept	ppe/ta	ln(s)	r&d/s	ebitda/ta	mtr
-0.63***	0.062	0.04*	-4.96***	1.65***	0.73***

$$CAR_i = \alpha_i + \beta\lambda_i + \varepsilon_i$$

Panel B: Estimation for the second step using the OLS regression model

N=695											
	Intercept	lambda	ppe/ta	ln(s)	r&d/s	ebitda/ta	mva/ta	mtr	bondrate	proceeds	P-value
Model 4.2	0.08	-0.14*									0.05
Model 4.3	-0.19	0.08	0.07	0.006	-0.54	0.28	-0.003	0.02	0.42	-0.07*	0.19
Model 4.4	-0.09		0.07	0.003	-0.28	0.19	-0.003	-0.02	0.43	-0.07**	0.14

Note: ppe denotes the plant, property and equipments; s denotes sales; r&d is research and development expenditures; mva denotes market-to-book ebitda denotes earnings before interest payments, tax and depreciation, amortisation; mtr is marginal tax rate, bondrate is 10-year T-bill rate 91 day to issuance announcement dates; CAR denotes cumulative abnormal returns, λ denotes Heckman's lambda; proceeds denotes issue size. Model 4.2 takes the form of CAR=f(lambda); Model 4.3 takes the form of CAR=f(X, lambda); Model 4.4 is CAR=f(X).

Table 4.5: Robustness testing results of Model 4.2.4.4

[illegible]

Note:

1. Model 4.2 takes the form of $CAR=f(\lambda da)$.
2. In Model 4.3, $CAR=f(\lambda da, X)$ is used; X stand for a vector of proxies for firm characteristics: ppe/ta proxies asset structure, $\ln(s)$ is size measurement; $r\&d/s$ denotes uniqueness; $ebitda/ta$ proxies profitability; mva/ta is the market-to-book ratio; mtr is marginal tax rate; $bondrate$ is 10-year T-bill rate; proceeds is the magnitude of debt funding; maturity refers to the maturity of long-term debt issuance.
3. Model 4.4 takes the form of $CAR=f(X)$;

Chapter 5

Conclusion

This thesis commences by relating the spurious ratio problem to empirical tests of capital structure theories. We use a variety of models and firstly show how sharing common divisors in multiple regression models may lead to misleading inferences. To address the spurious ratio problem, we use two panel models using levels instead of ratios and a probit model. Our results show these models act as better tools to find the determinants of capital structure. Last, the price impact of long-term debt issuances is investigated and zero price impact is found after considering self-selection using Heckman's (1979) two-step model.

Chapter 2 explores the spurious ratio problems caused by sharing common divisors in multiple regression models evidenced in the capital structure literature. Without correction, the estimated t-values and R-squares under traditional statistical inferences can yield misleading evidence of significant association between independent and dependent variables. In order to shed light on this problem, we show how the Monte-Carlo

simulation technique developed by Barraclough (2007) provides reliable statistical inferences when the parametric conventional inference is invalid. The second part of Chapter 2 further applies the same simulation procedures to two panel models using variables in levels instead of ratios, and no spurious ratio problem is evident. These two models are more appropriate to investigate capital structure theories after we consider the persistence character of capital structure (fixed effects) and endogeneity problems respectively. Results show changes on collateral assets, size, and r&d are positively associated to changes on debt values in the first differencing fixed effects model; and past debt level and size explain most of the current debt level in the dynamic system GMM model which suggests no significant relationship between debt level and firm characteristics.

Chapter 3 investigates the likelihood of long-term debt issuance using a probit model to overcome the spurious ratio problem evidenced in the traditional multiple regression models. With modifications to the Monte-Carlo simulation technique of Barraclough (2007), the cut-off values for slope coefficients, t-statistics and MacFadden's Pseudo R-squares are generated for the probit model. Our simulation based cut-off values are close to conventional levels which indicates no spurious ratio problem. It appears that the Monte-Carlo simulation method is a reliable method to verify parametric statistical inferences. By modeling the decision of debt issuance using a dichotomous variable, our results suggest leverage increasing firms tend to be larger, more profitable and firms with high r&d tend to be less likely to use debt as a means of financing.

Chapter 4 examines the price impact of straight long-term debt issuances using

Heckman's (1979) two-step approach in the US markets from 1986 to 2006. The matching firm method developed by Barber and Lyon (1996) is adopted to calculate abnormal returns with matching dimensions of industry and size. Testing the abnormal returns alone shows a significant negative price impact of debt announcements which appears to support the prediction of Miller and Rock (1986) that investors regard debt issuances as bad news. However, we show that once self-selection is controlled for, the negative price impact disappears in both our main tests and robustness tests. In addition, we find the price impacts rely on the benchmark being chosen; for example, there is a zero price impact when the CRSP equal-weighted market index is used, a positive impact when the CRSP value-weighted market index is used, and a negative impact when applying the matching firm approach. These different price impacts may reflect the unresolved empirical results in the literature. Although the signs for average abnormal returns differ according to the benchmark chosen, we come to the same conclusion that there is no significant price impact of long-term debt issuances once self-selection is accounted for.

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