# CHAPTER 3

# METHODOLOGY AND DATA

This section is divided into three parts. The first part discusses the various CAPM variants and two non-CAPM based models for estimating cost of equity. The second part provides a list of potential determinants as well as the expected relationship between these variables and the firm's cost of equity. The third part discusses the data and the procedures of analysis adopted for this study. The analysis of this study is basically divided into two parts: cost of equity measurement and cost of equity determinant analysis. Their results are reported separately in Chapter 4 and Chapter 5, respectively.

## 3.1 Measuring Cost of Equity

Modern financial economics assumes that the risk perception of investors is reflected in the cost of equity of the firm. Being risk-adverse, investors will demand a higher return when the perceived risk is larger. This transforms into a simple method for computing the firm's cost of equity by adding up the risk-free rate and the premium for systematic risk, which is the product of the beta for the firm ($\beta_i$) and the benchmark market risk premium, as follows:

Cost of Equity = (Risk-Free Rate) + (Risk Measure) x (Market Risk Premium)

or $$E(CE_i) = R_f + \beta_i \left(R_m - R_f\right) \qquad (3.1)$$

where $E(CE_i)$ represents the expected cost of equity for firm *i*; ($R_m - R_f$) represents the market risk premium; $R_m$ is the return on the benchmark market index; $R_f$ is the return on the risk-free asset; and $\beta_i$ measures the sensitivity of the firm returns to the benchmark market returns.

The above setting discounts out firm level unsystematic risk as investors believe that firm specific risks can be diversified away and hence should not be incorporated into the calculation of the cost of equity. What matters in evaluating firm performance is by looking at $\beta_i$, where conventionally it can be estimated via a CAPM where:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_t \tag{3.1a}$$

where $r_{it}$ is the excess return for firm *i*, that is, $(R_i - R_f)$; $r_{mt}$ is the excess return for the market portfolio, that is, $(R_m - R_f)$. The parameter $\alpha_i$ represents the intercept, and $\beta_i = \dfrac{\mathrm{cov}(r_{it}, r_{mt})}{\mathrm{var}(r_{mt})}$ is the beta regression coefficient capturing the sensitivity of the returns of firm *i* to the market risk.

The contribution of the CAPM is the idea of benchmarking the firm to the overall market or systematic risk – the co-movement of the firm's returns with the market returns. This is powerful in practice as it avoids the tedious calculation of risk measure in the modern portfolio theory that requires an extremely large portfolio covariance/correlation matrix for establishing an efficient portfolio. By benchmarking to the market, the calculation of risk involving $n$ firms measure is reduced from having to calculate the covariance matrix for $(n^2 - n)/2$ portfolios to only $n$ risk measures (the beta in equation 3.1a). In the case of 100 firms, instead of the covariance matrix for $(100^2 - 100)/2$ = 4,950 portfolios, we only need to find out the betas for 100 firms. This simplistic feature may be part of the reason for the widespread popularity of CAPM among practitioners despite the many debates associated with the use of market beta as the only factor that explains variation in stock returns.

Before emerging markets attracted the attention of international investor communities, the application of the CAPM for generating cost of equity estimates was based on the appraiser's belief of whether the world capital market is segmented or integrated. Depending on the choice, the variables used in the CAPM are different.

### 3.1.1 Local CAPM (LCAPM)

In its original form, the setting of the CAPM in equation (3.1) assumes the benchmark portfolio is the local market portfolio and that it is the only source of systematic risk for firms. This assumption is based on the segmented international financial market during the 1960s, when the model was developed. Thus, equation (3.1) can be regarded as a local CAPM (LCAPM, henceforth). Proponents of segmented world capital market may use the LCAPM to calculate the cost of equity for a firm. Equation (3.1) in a local setting is given by:

Cost of Equity = (Risk-Free Rate) +

(Local Risk Measure) x (Premium for Local Systematic Risk)

or $$E(CE_i) = R_F + \beta_i \left(R_M - R_F\right) \tag{3.2}$$

where $R_M$ is the return on the local market index and the risk measure $\beta_i$ is obtained by regressing a market model using time series of firm stock returns on the local market returns:

$$r_{it} = \alpha_i + \beta_i r_{Mt} + \varepsilon_t \tag{3.2a}$$

where $r_{it}$ is the actual return for firm $i$ and $r_{Mt}$ is the actual return for the local market portfolio. The parameter $\alpha_i$ and $\beta_i$ are the intercept and beta coefficient, respectively. Excess returns are not employed here as it is not the purpose of this study to test the validity of CAPM. Furthermore, the use of the market model does not affect the quality of the estimates. Hence, actual returns are used in the estimation of beta for this study.

### 3.1.2 Global CAPM (GCAPM)

With the fast development of world financial market after the 1980s, the world equity market has gained a high level of liberalization and integration. In a fully integrated global capital market, a firm's stockholders could be investors from many different countries because it is assumed that each of them holds a globally diversified portfolio. A global, classic CAPM could then be used in which the return premium to any investment, when measured in a specific currency unit, is the same for all investors. This is because the beta of each stock is measured with reference to the global capital market index and the market premium to be used is the global equity risk premium.

Extending equation (3.1) to a global setting, a global CAPM (GCAPM, henceforth) is given by:

Cost of Equity = (Global Risk-Free Rate) +

(Global Risk Measure) x (Premium for Global Systematic Risk)

or $$E(CE_i) = R_F^G + \beta_i^G \left(R_M^G - R_F^G\right) \quad (3.3)$$

where $R_F^G$ is the global risk-free rate, $R_M^G$ the global portfolio return, and $\beta_i^G$ is obtained by regressing firm returns on the global market returns:

$$r_{it} = \alpha_i^G + \beta_i^G r_{Mt}^G + \varepsilon_t \quad (3.3a)$$

where $r_{Mt}^G$ is the return for the global market portfolio. The parameter $\alpha_i^G$ and $\beta_i^G$ are the intercept and beta coefficient, respectively.

### 3.1.3 Two-factor CAPM (2F-CAPM)

The preceding sections have discussed the CAPM under two extreme assumptions, that is, either the world capital market is fully segmented or is fully integrated. Tests of the classic CAPM under the hypothesis of full market integration have rejected a single source of risk as being adequate in describing cross-section variations of returns across different countries (see Harvey, 1991). This rejection could mean that the world capital market is not integrated. Driven by the belief that the world capital market is probably neither fully segmented nor fully integrated, as well as the findings of Bekaert and Harvey (1995) and Bekaert *et al.* (2005) that some emerging markets are partially integrated with global capital markets, this study proposes a two-factor model which introduces a global market factor into the classic CAPM, hereafter denoted as 2F-CAPM.[5]

The 2F-CAPM includes both types of premium, one for the stock's exposure to the return on the local market portfolio and another for the exposure to the return on the global market portfolio. Therefore, the model captures the sensitivity of a firm's returns not only to the local market movements, but also to the global market movements. The cost of equity under the 2F-CAPM is given by:

Cost of Equity = (Risk-Free Rate) + (Local Risk Measure) x
(Premium for Local Systematic Risk) +
(Global Risk Measure) x (Premium for Global Systematic Risk)

or
$$E(CE_i) = R_F + \beta_{Li}\left(R_M - R_F\right) + \beta_{Gi}\left(R_M^G - R_F^G\right) \tag{3.4}$$

Note that $\beta_{Li}$ and $\beta_{Gi}$ in equation (3.4) are denoted differently from the $\beta$ coefficients in equations (3.2) and (3.3). This is to highlight the fact that they are coefficients measuring partial sensitivity of firm returns to the local and global market movements, respectively.

[5] A two-factor setting is common in the literature of asset pricing for partially integrated markets. However, there are a few different approaches to deal with partially integrated pricing models, see for example, Errunza and Losq (1985), Errunza *et al.* (1992), Kearney (2000) and Gérard *et al.* (2003).

The beta estimation for the 2F-CAPM is based on the following model:

$$r_{it} = \alpha_i + \beta_{Li} r_{Mt} + \beta_{Gi} r_{Mt}^{G} + \varepsilon_t \qquad (3.4a)$$

In conjunction with the findings of Estrada (2002) and Chen and Chen (2004) that downside beta has a stronger explanatory power on stock returns than standard beta, this study proposes a downside version of the LCAPM, GCAPM and 2F-CAPM, where the risk measures in equation (3.2), (3.3) and (3.4) are replaced with downside beta. The downside models are discussed in more details in the following section.

### 3.1.4 Downside LCAPM (DLCAPM)

The calculation of downside beta involves isolating instances when the firm and the local market index returns are less than zero. In the LCAPM framework as in equation (3.2), the cost of equity calculation utilizing the downside beta approach is denoted as DLCAPM and the equation becomes:

Cost of Equity = (Risk-Free Rate) +

(Downside Local Risk Measure) x (Premium for Local Systematic Risk)

or $$E(CE_i) = R_F + \beta_i^D \left(R_M - R_F\right) \qquad (3.5)$$

where $\beta_i^D$ is the downside local risk measure, and this is the only component that differentiates equation (3.5) from equation (3.2).

To obtain the downside risk measure or downside beta, two new 'downside' series $r_{it}^D$ and $r_{Mt}^D$ are generated to replace $r_{it}$ and $r_{Mt}$, respectively. These two downside series are the firm and market returns that have value less than zero[6]. These two newly

[6] Chen and Chen (2004) found that downside risk measure relative-to-zero return rate, which is a measure relative to investors' net wealth effect, has stronger power in explaining future returns than downside risk measure relative-to-mean return rate (a measure

generated downside series are $r_{it}^{D} = \min(r_{it}, 0)$ and $r_{Mt}^{D} = \min(r_{Mt}, 0)$, respectively (see Estrada, 2002). The beta that is obtained from the regression of these two new series is called 'downside beta', denoted as $\beta_i^D$. The regression to obtain the downside local risk measure is given by:

$$r_{it}^{D} = \alpha_i^D + \beta_i^D r_{Mt}^{D} + \varepsilon_t \tag{3.5a}$$

where $\beta_i^D = \dfrac{\operatorname{cov}\left(r_{it}^{D}, r_{Mt}^{D}\right)}{\operatorname{var}\left(r_{Mt}^{D}\right)}$

### 3.1.5 Downside GCAPM (DGCAPM)

Using Estrada's approach, the downside risk model can be extended to the GCAPM. The rationale is that even if the market is globally integrated, investors might still have a preference for asymmetric risk. The downside version of the GCAPM where we termed as DGCAPM is shown below:

Cost of Equity = (Global Risk-Free Rate) +

(Downside Global Risk Measure) x

(Premium for Global Systematic Risk)

or

$$E(CE_i) = R_F^G + \beta_i^{DG}\left(R_M^G - R_F^G\right) \tag{3.6}$$

where $\beta_i^{DG}$ is the downside global risk measure.

The regression to obtain the downside global risk measure for this model is given by:

$$r_{it}^{D} = \alpha_i^{DG} + \beta_i^{DG} r_{Mt}^{DG} + \varepsilon_t \tag{3.6a}$$

where $r_{Mt}^{DG}$ is the return for global market portfolio that has value less than zero. This new downside series is $r_{Mt}^{DG} = \min\left(r_{Mt}^{G}, 0\right)$. The downside global beta coefficient is then given by:

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relative to the market performance). This finding is consistent with their hypothesis that investors are more concerned with their net wealth effect than the market relative performance.

$$\beta_i^{DG} = \frac{\mathrm{cov}\left(r_{it}^{D}, r_{Mt}^{DG}\right)}{\mathrm{var}\left(r_{Mt}^{DG}\right)}$$

### 3.1.6 Two-factor Downside CAPM (2F-DCAPM)

We also propose a downside version of the two-factor CAPM to calculate cost of equity. This is an extension from equation (3.4) and is given by:

Cost of Equity = (Risk-Free Rate) + (Downside Local Risk Measure) x

(Premium for Local Systematic Risk) +

(Downside Global Risk Measure) x

(Premium for Global Systematic Risk)

or $$E(CE_i) = R_F + \beta_{Li}^{D}\left(R_M - R_F\right) + \beta_{Gi}^{D}\left(R_M^{G} - R_F^{G}\right) \quad (3.7)$$

where $\beta_{Li}^{D}$ is the downside local beta and $\beta_{Gi}^{D}$ the downside global beta. These beta coefficients are obtained from the regression given by:

$$r_{it}^{D} = \alpha_i^{D} + \beta_{Li}^{D}\left(r_{Mt}^{D}\right) + \beta_{Gi}^{D}\left(r_{Mt}^{DG}\right) + \varepsilon_t \quad (3.7a)$$

where

$$\beta_{Li}^{D} = \frac{E\left[\min\left(r_{Mt}^{G},0\right)\right]^2 E\left[\min\left(r_{it},0\right)\min\left(r_{Mt},0\right)\right] - E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right]E\left[\min\left(r_{it},0\right)\min\left(r_{Mt}^{G},0\right)\right]}{E\left[\min\left(r_{Mt},0\right)\right]^2 E\left[\min\left(r_{Mt}^{G},0\right)\right]^2 - \left[E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right]\right]^2}$$

$$\beta_{Gi}^{D} = \frac{E\left[\min\left(r_{Mt},0\right)\right]^2 E\left[\min\left(r_{it},0\right)\min\left(r_{Mt}^{G},0\right)\right] - E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right]E\left[\min\left(r_{it},0\right)\min\left(r_{Mt},0\right)\right]}{E\left[\min\left(r_{Mt},0\right)\right]^2 E\left[\min\left(r_{Mt}^{G},0\right)\right]^2 - \left[E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right]\right]^2}$$

### 3.1.7 The Non-CAPM Cost of Equity: Estrada Model

Existing empirical evidence has questioned the validity of the classical CAPM for applications in emerging markets. For example, Harvey (1995) and Estrada (2000) showed that standard betas are not correlated with returns computed for the world market. In addition, the beta values seem to be too small to reflect cost of equity that most investors deem as reasonable. These problems have led some scholars to look for measures of risk beyond the realm of CAPM. One of such alternatives is offered in Estrada (2000, 2001).

In the application of the classical one-factor CAPM, beta coefficient is used as the only risk measure in the calculation of cost of equity. However, Estrada (2000, 2001) argued that the standard beta is not appropriate for estimating the cost of equity for emerging markets and suggested several risk variables such as total risk as measured by the standard deviation of returns, and downside risk as measured by the semi-deviation of returns and downside beta. The application of downside beta in calculating cost of equity has been shown in equations (3.5), (3.6) and (3.7). The measures using standard deviation and semi-deviation of returns are discussed next.

***(i) Standard Deviation of Returns (Total Risk)***

From a local investor perspective, the general framework of Estrada's model can be given as:

Cost of Equity = (Risk-Free Rate) + (Total Risk Measure) x
(Premium for Total Risk)

or $$E(CE_i) = R_f + \sigma_i \left(R_m - R_f\right) \qquad (3.8)$$

The total risk for the stock returns of any particular firm is basically given by the simple standard deviation of the return series, $\sigma_{\mathrm{i}} = \sqrt{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left(r_{it} - \overline{r_i}\right)^2}$ (3.8a)

where $T$ is the total number of observations and $\overline{r_i} = \frac{1}{\mathrm{T}}\sum_{t=1}^{T} r_{it}$ .

(***ii) Semi-Deviation of Returns (Downside Risk)***

Using downside risk as risk measure is not a new concept. It was first suggested by Roy (1952) who believed investors will prefer safety of principal first and will set some minimum acceptable return that will preserve the principal. Roy's concept became influential in the development of downside risk measures. The cost of equity measure for this model can be written as:

Cost of Equity = (Risk-Free Rate) + (Downside Risk Measure) x

(Premium for Downside Risk)

or $$E(CE_i) = R_f + \delta_{R_{ft},i}\left(R_m - R_f\right) \quad (3.9)$$

The semi-deviation measures the average deviation of returns below zero:

$$\delta_{R_{ft},i} = \sqrt{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left(\min r_{it}, 0\right)^2} \quad (3.9a)$$

The $\delta_{R_{ft},i}$ measure obtained is then applied to equation (3.8) in replacement of $\sigma_{\mathrm{i}}$ to calculate the firm-level cost of equity.

## 3.2 Selection of the Best Risk Measure

Previous sections have proposed eight different risk measures for application in the calculation of cost of equity. We are interested to find one risk measure that gives the best fit to calculate the firm's cost of equity. Previous literature, including Estrada (2000, 2001, 2002) and Chen and Chen (2004) have used the risk-return approach to compare the performance of several risk measures investigated. They estimated either a cross section regression (see Estrada, 2000, 2001, 2002) or a pooled regression (see Chen and Chen, 2004) of the actual stock returns which reflect the ex-post cost of equity on each of the various risk measures under investigation, and then refers to the coefficient of determination ($R^2$) of the model to decide the best risk measure.

We follow this approach and estimate the following pooled regression of the actual firm stock returns on the risk measure:

$$r_{it} = \gamma_0 + \gamma_1 \beta_{it}^{panel} + \varepsilon_{it} \tag{3.10}$$

where $i$=1,2,...,n, n is the number of firms; $t$=1,2,...,T; $r_{it}$ is the panel stack series of the actual realized ex-post firm stock returns; $\beta_{it}^{panel}$ represents the panel stack series of the risk measure; and $\gamma_0$ and $\gamma_1$ are the panel regression coefficients.

The $R^2$ of model (3.10) is basically the sum of square of the regression divided by the total sum of square of the model, given by:

$$R^2 = \frac{\sum\left(\hat{R}_{it} - \overline{R}\right)^2}{\sum\left(R_{it} - \overline{R}\right)^2}$$

where $\hat{R}_{it}$ is the fitted or the estimated value of the firm stock returns from model (3.10).

In the view that some models have two betas and some have one beta, the adjusted $R^2$ of the models were recorded and used as the selection criterion to find out which of the risk measures has the highest explanatory power. The advantage of referring to adjusted $R^2$ value is that it only increases if the additional beta improves the model more than would be expected by chance. The adjusted $R^2$ is given by:

$$\overline{R}^2 = 1 - \left(1 - R^2\right)\frac{n-1}{n-k-1}$$

where $n$ is the number of observations and $k$ is the total number of regressors. The empirical models used in this study are summarized in Table 3.1.

### 3.3 Determinants of Cost of Equity

After we identify the model with the best fit for calculating cost of equity, we proceed to investigate the potential determinant(s) of the firm's cost of equity on a sectoral basis. From the literature reviewed in Chapter 2, in general, firm-specific factors can be categorized into two; variables measured based on accounting information only (accounting-based) and variables measured based on relations between market data and accounting data (market-based). These variables are actually financial ratios which are taken from a firm's income statement, balance sheet, or both. The use of financial ratios is popular because they enable interested parties to make relative comparisons of firm performance across different firms (cross-section analysis) or over time (time-series analysis).

Financial ratios are discussed in almost every basic finance textbooks and are divided into five basic categories for convenience. They are debt, activity, liquidity, profitability, and market ratios. Debt, activity and liquidity ratios mainly measure the risk factor of a firm. For example, debt ratios give indication on the debt position of a firm and the ability of the firm to service interest payments. Ratios under "liquidity" are often regarded as good leading indications of a firm's cash flow. Low or declining liquidity could be a signal of financial distress and even precursor to bankruptcy. Last but not least, activity ratios show the efficiency of a firm in converting its various asset accounts, including inventory, into sales or cash. More often, activity ratios are used as a yardstick on the efficiency of a firm in allocating its resources.

On the other hand, ratios related to profitability are some measure of returns. The profitability ratios enable evaluation on a firm's profits with respect to sales, assets or its equity holders' investment. Appraisers will be able to gauge how well a firm makes investment and financing decisions. Market ratios are the only group in the five categories which capture both the risk and return factor of a firm. The market ratios also differ from the previous four groups of ratio in that they are market-based while the others are accounting-based. These market-based ratios provide insights into the assessment of investors in the marketplace on the firm performance in terms of risk and return. Should the firm's accounting ratios suggest that the firm has higher risk than its industry average, this information ought to be reflected in a lower stock price.

Since each debt, activity, liquidity, profitability, and market categories can be measured by few different financial ratios, we choose one ratio to represent each category. The selection is based on those previously used in the literature. As the number of potential determinants of cost of equity is overwhelming, we only choose the most cited or employed variable for each category. A total of seven potential independent variables have been identified. The additional two variables are firm size and stock liquidity which are shown to have a significant effect on the variations of cost of equity.

We consider seven variables where the first four variables (CR, DE, EPS and TAT as explained below) are characterized as accounting-based and the last three variables (MB, SIZE and SL as explained below) are characterized as market-based. The determinants and the hypothesized relationship of these variables with cost of equity are discussed in detail in the sub-sections below.

**Accounting-based variables:**

a) Current Ratio, CR (positive/negative): Current ratio is normally used as an indication of the firm's ability to fulfil short-term obligations. Higher current ratio means the firm has more short-term assets (cash, receivables, and inventory) and hence is more capable to pay off its obligations as they are due. High liquidity also ensures that the firm is able to take on profitable investment when they become available. On the other hand, it could also mean inefficient use of funds. So it is debatable whether the sign should be positive or negative. Omran and Pointon (2004) found current ratio to be a significant factor in explaining cost of equity. Their results showed that higher current ratio is related to lower cost of equity. CR is defined as total current assets divided by total current liabilities.

b) Debt-to-Equity Ratio, DE (positive): Debt-to-equity ratio measures the amount of a firm's debt financing in relative to its equity financing. Modigliani and Miller (1958, 1963) established that cost of equity is a function of leverage (debt-to-equity ratio) and taxes (corporate and individual level). Expanding the study of Modigliani and Miller, Dhaliwal *et al.* (2006) provided evidence that cost of equity is negatively associated with corporate taxes but positively related to personal taxes. Ameer (2007) argued that the advantage provided by interest expense deduction diminishes after a certain point, and the additional financial risk associated with higher debt level outweighs the lower nominal cost of debt, thereby increasing the cost of equity. When a firm's financial risk increases, cost of equity also increases. DE is defined as total debt divided by common equity.

c) Earnings per Share, EPS (positive): Earnings per share have similar effect as dividend yield according to Fama and French (1988). The notion of using dividend yield to forecast returns is not new. Evidence to support the notion can be found in the study of Rozeff (1984), Campbell and Shiller (1988), Fama and French (1988) and Campbell (1991), among many others. Their findings are in accord with the intuition that stock prices are low relative to dividends when discount rates (cost of equity) and expected returns are high. Therefore, a positive relationship between earnings per share and cost of equity is expected. EPS is defined as earnings available for common stockholders divided by number of shares outstanding.

d) Total Asset Turnover Ratio, TAT (negative): Ang *et al.* (2000) argued that asset turnover ratio measures the efficiency of management in utilizing assets. Firms with higher asset turnover ratio have lower cost of equity in the framework of Ang *et al.* (2000) because it is a reflection of lower managerial agency problem. Their findings are supported by Singh and Nejadmalayeri (2004) who suggested that managerial efficiency in utilization of firm resources has a positive effect on cost of equity. TAT is defined as total sales divided by total assets.

**Market-based variables:**

e) Market-to-Book Ratio, MB (negative): Fama and French (1993) showed that book-to-market ratio is an important valuation measure for explaining average stock returns. The ratio may act as a proxy for distress risk factor since financially distressed firms are likely to have high book-to-market ratio. Gode and Mohanram (2003) also pointed out that higher book-to-market ratio reflects higher perceived risk. Ameer (2007) documented that book-to-market ratio is positively correlated to cost of equity. This study uses the market-to-book ratio available from Datastream. Following Guedhami and Mishra (2009), a negative relation is expected. MB is defined as the market value of the ordinary (common) equity divided by the balance sheet value of the ordinary (common) equity.

f) Firm Size, SIZE (negative): The well-known effect of firm size on stock return variations is first embedded in Fama and French's (1993) three-factor model. They found small firms have higher average returns than those of the large firms. Bloomfield and Michaely (2004) reported that analysts expect large firms to have slightly less risk and therefore there should be a negative relationship between size and the cost of equity. Hail and Leuz (2006) also found a significant negative relationship between firm size and the cost of equity. SIZE is defined as the natural logarithm of market value of a firm's outstanding common stock at the end of each year.

g) Stock liquidity, SL (negative): Stock liquidity is an important attribute since highly liquid stocks can be bought and sold with minimal impact on stock prices. On the contrary, an illiquid stock will increase cost of trading because of the difficulty to trade the stocks. The influence of trading costs on investors' required returns was examined by Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996) and Jacoby *et al.* (2000). Their studies indicate a direct link between liquidity and cost of equity. Following Brennan *et al.* (1998) and Chordia *et al.* (2001), the natural logarithm of annual trading volume is used as the proxy for SL.

Table 3.1: Model Summary for the Study

| **Model** | **Risk Measure** |
|---|---|
| **LCAPM** [equation (3.2)]: $E(CE_i) = R_F + \beta_i(R_M - R_F)$ | $r_{it} = \alpha_i + \beta_i r_{Mt} + \varepsilon_t$, where $\beta_i = \dfrac{\operatorname{cov}(r_{it}, r_{Mt})}{\operatorname{var}(r_{Mt})}$ |
| **GCAPM** [equation (3.3)]: $E(CE_i) = R_F^G + \beta_i^G\left(R_M^G - R_F^G\right)$ | $r_{it} = \alpha_i^G + \beta_i^G r_{Mt}^G + \varepsilon_t$, where $\beta_i = \dfrac{\operatorname{cov}\left(r_{it}, r_{Mt}^G\right)}{\operatorname{var}\left(r_{Mt}^G\right)}$ |
| **2F-CAPM** [equation (3.4)]: $E(CE_i) = R_F + \beta_{Li}(R_M - R_F) + \beta_{Gi}\left(R_M^G - R_F^G\right)$ | $r_{it} = \alpha_i + \beta_{Li} r_{Mt} + \beta_{Gi} r_{Mt}^G + \varepsilon_t$, where $\beta_{Li} = \dfrac{E\left(r_{Mt}^G\right)^2 E(r_{it}, r_{Mt}) - E\left(r_{Mt}, r_{Mt}^G\right) E\left(r_{it}, r_{Mt}^G\right)}{E\left(r_{Mt}\right)^2 E\left(r_{Mt}^G\right)^2 - \left[E\left(r_{Mt}, r_{Mt}^G\right)\right]^2}$, $\beta_{Gi} = \dfrac{E\left(r_{Mt}\right)^2 E\left(r_{it}, r_{Mt}^G\right) - E\left(r_{Mt}, r_{Mt}^G\right) E\left(r_{it}, r_{Mt}\right)}{E\left(r_{Mt}\right)^2 E\left(r_{Mt}^G\right)^2 - \left[E\left(r_{Mt}, r_{Mt}^G\right)\right]^2}$ |
| **DLCAPM** [equation (3.5)]: $E(CE_i) = R_F + \beta_i^D(R_M - R_F)$ | $r_{it}^D = \alpha_i^D + \beta_i^D r_{Mt}^D + \varepsilon_t$, where $\beta_i^D = \dfrac{\operatorname{cov}\left(r_{it}^D, r_{Mt}^D\right)}{\operatorname{var}\left(r_{Mt}^D\right)}$ |
| **DGCAPM** [equation (3.6)]: $E(CE_i) = R_F^G + \beta_i^{DG}\left(R_M^G - R_F^G\right)$ | $r_{it}^D = \alpha_i^{DG} + \beta_i^{DG} r_{Mt}^{DG} + \varepsilon_t$, where $\beta_i^{DG} = \dfrac{\operatorname{cov}\left(r_{it}^D, r_{Mt}^{DG}\right)}{\operatorname{var}\left(r_{Mt}^{DG}\right)}$ |

Table 3.1, continued.

| **Model** | **Risk Measure** |
|---|---|
| **2F-DCAPM** [equation (3.7)]: $E(CE_i) = R_F + \beta_{Li}^{D}\left(R_M - R_F\right) + \beta_{Gi}^{D}\left(R_M^G - R_F^G\right)$ | $r_{it}^{D} = \alpha_i^{D} + \beta_{Li}^{D}\left(r_{Mt}^{D}\right) + \beta_{Gi}^{D}\left(r_{Mt}^{DG}\right) + \varepsilon_t$ , where $\beta_{Li}^{D} = \frac{E\left[\min\left(r_{Mt}^{G},0\right)\right]^2 E\left[\min\left(r_{it},0\right)\min\left(r_{Mt},0\right)\right] - E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right] E\left[\min\left(r_{it},0\right)\min\left(r_{Mt}^{G},0\right)\right]}{E\left[\min\left(r_{Mt},0\right)\right]^2 E\left[\min\left(r_{Mt}^{G},0\right)\right]^2 - \left[E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right]\right]^2}$ $\beta_{Gi}^{D} = \frac{E\left[\min\left(r_{Mt},0\right)\right]^2 E\left[\min\left(r_{it},0\right)\min\left(r_{Mt}^{G},0\right)\right] - E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right] E\left[\min\left(r_{it},0\right)\min\left(r_{Mt},0\right)\right]}{E\left[\min\left(r_{Mt},0\right)\right]^2 E\left[\min\left(r_{Mt}^{G},0\right)\right]^2 - \left[E\left[\min\left(r_{Mt},0\right)\min\left(r_{Mt}^{G},0\right)\right]\right]^2}$ |
| **Estrada's models:** ***Standard Deviation*** [equation (3.8)]: $E(CE_i) = R_f + \sigma_i\left(R_m - R_f\right)$ ***Semi-Deviation*** [equation (3.9)]: $E(CE_i) = R_f + \delta_{R_{ft},i}\left(R_m - R_f\right)$ | $\sigma_{\mathrm{i}} = \sqrt{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left(r_{it} - \overline{r_i}\right)^2}$ $\delta_{R_{ft},i} = \sqrt{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left[\min\left(r_{it},0\right)\right]^2}$ |

### 3.4 The Panel Models for Examining the Determinants of Cost of Equity

To investigate the determinants of cost of equity, a panel regression approach is more efficient and informative. A panel regression not only provides spatial and temporal dimension of the longitudinal data, it also has the capacity to handle larger sample size and therefore gives higher degrees of freedom, more precise estimators, and greater statistical test power. The specification in panel regression also allows for greater flexibility to account for sophisticated behavioural effects and it imposes less restrictive assumptions compared to the usual linear regression. With panel setting, the spatial dimension of Malaysian firms as well as the time span dynamics over the sample period can be incorporated into a single model. Different panel models are considered and they are discussed below.

#### 3.4.1 The Fixed Effect Model

We can express our model for determinants of cost of equity in a panel structure as follows:

$$Y_{it} = \alpha_{it} + X'_{it}\beta + \varepsilon_{it} \qquad i = 1,...,N \text{ and } t = 1,...,T \tag{3.11}$$

where $Y_{it}$ denotes the cost of equity for firm *i* and year *t*, $\beta$ is a vector of *k*x1 coefficients and $X_{it}$ is a vector of *k*x1 determinant variables. The term $\varepsilon_{it}$ is referred to as idiosyncratic or time varying error and it is assumed to capture all the unobserved factors that change over time and affect $Y_{it}$. The panel series in the above equation are stacked by firm as a unit of panel containing all the *T* observations. Pooling (stacking) the time series and cross-section data only raises little statistical complications to applying Ordinary Least Squares (OLS) estimators if the regression relationship is assumed to remain constant over space and time. OLS provides consistent and efficient scalar estimates of the common intercept and slope coefficient. This means we can run a simple regression on the panel dataset, preserving all the linear regression assumptions.

However, in setting the panel determinant model for cost of equity, it is only fair to assume that firms are behaving differently. The unobservable characteristics, such as brand name, patent rights, monopoly power, managerial competency and worker quality which are all constant over time, or at least in the short run, are likely to differ across firms. These time-invariant firm heterogeneity factors are likely to affect the cost of equity when we stack many firms as a panel series. They can be modelled as follows:

$$Y_{it} = \alpha_{it} + X_{it}'\beta + \eta_i + \varepsilon_{it} \tag{3.12}$$

where $\eta_i$ is the unobserved heterogeneity across firm $i$ but invariant over time $t$. In panel regression, these are called the fixed effects or unobserved effects. If these factors are uncorrelated with the explanatory variables then we can safely apply the pooling method with OLS estimator on the above equation. However, if these factors are correlated with the explanatory variables, pooled OLS is biased and inconsistent. One way of getting rid of these fixed effects is to difference the data across years, as follows:

$$(Y_{it} - Y_{it-1}) = (\alpha_{it} - \alpha_{it-1}) + (X_{it} - X_{it-1})'\beta + (\eta_i - \eta_i) + (\varepsilon_{it} - \varepsilon_{it-1}) \tag{3.13}$$

We can then apply the OLS to estimate the following model:

$$\Delta Y_{it} = \delta_{it} + \Delta X_{it}'\beta + \Delta\varepsilon_{it} \tag{3.13a}$$

The OLS estimator on the above equation is called the first-differenced estimator and in this setting we allow the explanatory variables to correlate with the unobserved firm heterogeneity. Two consequences arise with this estimator; we will lose one period of data point in taking the first difference, and the variation in the series is greatly reduced and hence a larger coefficient standard error is expected.

Another way to eliminate the fixed effect is to use the fixed effect transformation, where the following transformation is done:

$$(Y_{it} - \overline{Y}_i) = (\alpha_{it} - \overline{\alpha}_i) + (X_{it} - \overline{X}_i)'\beta + (\eta_i - \overline{\eta}_i) + (\varepsilon_{it} - \overline{\varepsilon}_i) \tag{3.14}$$

where $\bar{Y}_i = \frac{1}{T}\sum_{t=1}^{T} Y_{it}$

$$\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$$

$$\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{i,t}$$

or alternatively:

$$\ddot{Y}_{it} = \ddot{\alpha}_{it} + \ddot{X}'_{it}\beta + \ddot{\varepsilon}_{it} \tag{3.14a}$$

where $\ddot{Y}_{it} = (Y_{it} - \bar{Y}_i)$ is the time demeaned data on *Y*, and similarly for $\ddot{X}_{it}$ and $\ddot{\varepsilon}_{it}$. With this transformation, the unobserved effect has been moved out.

As we are transforming the series with deviation from the mean within each cross-section (firm) observation, this transformation is also called the within transformation. The transformation basically applies the within sum of squares as in the analysis of variance framework. Applying OLS on this transformed equation is called the within estimator or more popularly known as the fixed effect estimator. The within estimator is unbiased if the idiosyncratic error is uncorrelated with the explanatory variables but it also allows for arbitrary correlation between $\eta_i$ and the explanatory variables, as the first-differenced estimator. The error term $\ddot{\varepsilon}_{it}$ follows the classical IID assumptions with mean zero and constant variance. Note that under this setting, the fixed effect model cannot accommodate any other time-invariant explanatory variable, as they will be swept away by the fixed effect transformation.

Another way to estimate the fixed-effect estimator is using a dummy variable approach. This approach assumes that the firm effects can be captured by introducing multiple intercept to capture the time-invariant firm effect. We can introduce *i*-1 number of intercepts if the model has a constant term to avoid the dummy variable trap as in the following:

$$Y_{it} = \alpha_{it} + X'_{it}\beta + D'_i\eta_i + \varepsilon_{it} \qquad (3.15)$$

where $D_i$ is the vector of dummy variables assigned to each firm. The OLS estimator from this setting is called the *Least Squares Dummy Variable* (LSDV) estimator. The problem with LSDV estimator is with the large number of dummy variables needed when firm number increases. The degrees of freedom of the regression will fall sharply with increasing number of parameters to be estimated.

Both first-differenced estimator and fixed-effect estimator are unbiased and also consistent as $N$ increases to infinity. So the only criterion we can use to compare them is on the relative efficiency of these estimators, and this can be determined by the serial correlation test on the idiosyncratic errors. If the idiosyncratic error is correlated, then the fixed-effect estimator is more efficient. As whether a fixed effect model is needed, basically an F-test can be conducted.

### 3.4.2 The Random Effect Model

Similar to the firm effect, the panel cost of equity equation is also likely to change across year (time) as the general business condition might be different from year to year. We can extend equation (3.12) to incorporate a period-specific effect, specified as:

$$Y_{it} = \alpha_{it} + X'_{it}\beta + \eta_i + \xi_t + \varepsilon_{it} \qquad (3.16)$$

where $\xi_t$ captures the period effects. Adding the period effects is equivalent to adding dummy variables $D'_t\xi_t$. This model is referred to as a two-way fixed effect model, henceforth. A one-way fixed effect model is referring to model with only firm effect or period effect.

If the unobservable firm heterogeneity is uncorrelated with any of the explanatory variables, then using the fixed effect transformation results in inefficient estimators. In this case, we can actually apply another type of model called the random effect model. Random effect model is basically an error decomposition model that treats firm and time heterogeneity $\eta_i$ and $\xi_t$ as part of the error terms. In other words, the random effect model assumes the firm and time intercepts as a function of a mean value plus a random error, and they must be uncorrelated with the regressors. A two-way error component random effect model can be written as:

$$Y_{it} = \mu + X'_{it}\beta + v_{it} \tag{3.17}$$

where $v_{it} = \eta_i + \xi_t + \varepsilon_{it}$

$$E\eta_i = E\xi_t = E\varepsilon_{it} = 0,$$

$$E\eta_i\xi_t = E\eta_i\varepsilon_{it} = E\xi_t\varepsilon_{it} = 0,$$

$$E\eta_i\eta_j = \begin{cases} \sigma_\eta^2 & \text{if } i = j, \\ 0 & \text{if } i \neq j, \end{cases}$$

$$E\xi_t\xi_s = \begin{cases} \sigma_\xi^2 & \text{if } t = s, \\ 0 & \text{if } t \neq s, \end{cases}$$

$$E\varepsilon_{it}\varepsilon_{js} = \begin{cases} \sigma_v^2 & \text{if } i = j,\ t = s, \\ 0 & \text{otherwise}, \end{cases}$$

$$E\eta_i X'_{it} = E\xi_t X'_{it} = E\varepsilon_{it} X'_{it} = 0$$

Both $\eta_i$ and $\xi_t$ are now random firm and period error terms with a mean value of zero and variance of $\sigma_\eta^2$ and $\sigma_\xi^2$, respectively. They are not directly observable and thus are a form of latent variable (Hsiao, 2003). The variance component of the dependent variable, $\sigma_C^2$, can be decomposed into:

$$\sigma_C^2 = \sigma_\eta^2 + \sigma_\xi^2 + \sigma_\varepsilon^2 \tag{3.18}$$

If $\sigma_\eta^2$ and $\sigma_\xi^2$ are both zero, there is no distinction between the random effect model and a simple pooled regression. In the above specification, the disturbance terms $\varepsilon_{it}$ and $\varepsilon_{is}$ for $t \neq s$ can be correlated. The correlation coefficient, $corr(\varepsilon_{it}, \varepsilon_{is})$, is given as:

$$corr(\varepsilon_{it}, \varepsilon_{is}) = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\varepsilon^2} \tag{3.19}$$

The usual OLS estimator becomes inefficient in the presence of autocorrelation. To overcome the autoregressive correlation problem, we can use Generalized Least Squares (GLS) to estimate the model, provided we have a large *N* and relatively small *T*. The GLS transformation basically is to run the following model:

$$(Y_{it} - \lambda \overline{Y}_i) = \alpha(1-\lambda) + (X_{it} - \lambda \overline{X}_i)'\beta + (v_{it} - \lambda \overline{v}_i) \tag{3.20}$$

where $\lambda = 1 - \left[\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\eta^2}\right]^{\frac{1}{2}}$

The GLS basically is a quasi-demeaned transformation, which subtracts a fraction of the time average, where the fraction depends on $\sigma_\eta^2$, $\sigma_\varepsilon^2$ and *T*. The feasible GLS estimator is known as the random effect estimator. The random effect estimator is consistent and asymptotically normally distributed as *N* gets large with fixed *T*. However, under the quasi-demeaned transformation $(Y_{it} - \lambda \overline{Y}_i)$ could be correlated with $(v_{it} - \lambda \overline{v}_i)$ because $v_i$ is correlated with $Y_{it}$, and then the GLS estimator will be biased. There are several ways to correct for this bias. The system GMM estimator to be discussed in the coming sub-section is one of the best choice. The random effect model basically is a generalization of the pooled and fixed effect model. Pooled regression estimator is obtained when $\lambda = 0$ and fixed-effect estimator is obtained when $\lambda = 1$. So when $\lambda$ gets close to 1, random effect estimator tends to be the fixed-effect estimator. If $\lambda$ gets close to zero, we get close to the pooled estimators.

### 3.4.3 The Dynamic Panel Model with GMM Estimators

If there is autocorrelation in the cost of equity modeling, then a dynamic panel model is necessary to deal with it. Although there are many types of autocorrelation in panel data, generally, a temporal autocorrelation on lags of the residuals can be used to infer on the autocorrelation problem. As in time series model, we can introduce the lagged dependent variable to take care of the autocorrelation problem but in panel setting, the autoregressive setting is a bit complicated.

A popular autoregressive panel model or the dynamic panel model is attributed to Arellano and Bond (1991). The Arellano-Bond dynamic panel model basically applies the GMM estimator with the instrumental variable approach, but one assumption of this model is the temporal span must be greater than the number of regressors in the model, which is suitable for the setting of the cost of equity equation we use.

Consider a panel model with a lagged dependent variable:

$$Y_{it} = \mu_{it} + \alpha Y_{it-1} + \sum \beta X_{it} + v_{it} \tag{3.21}$$

where $v_{it} = \eta_i + \varepsilon_{it}$ and $E[\eta_i] = E[\varepsilon_{it}] = E[\eta_i \varepsilon_{it}] = E[\varepsilon_{it}\varepsilon_{js}] = 0$ for $i \neq j$ and $t \neq s$.

We can then estimate the following the first-differenced equation to remove the firm specific heterogeneity:

$$\Delta Y_{it} = \delta_{it} + \alpha \Delta Y_{it-1} + \sum \beta \Delta X_{it} + \Delta v_{it} \tag{3.22}$$

The transformed error term however is now correlated with the lagged dependent variable. Also, there is a problem of dependence of $\Delta v_{it}$ and $\Delta v_{it-1}$, implying OLS estimates are inconsistent. A two-stage least square (2SLS) method with instrument variables that are both correlated with $\Delta Y_{it-1}$ and orthogonal to $\Delta v_{it}$ can produce a consistent estimator provided $T \geq 3$. When we have more than three time series observations, additional instruments are available. For example, for *t*=3, $Y_{i1}$ can be used as the instrument, but when *t*=4, both $Y_{i1}$ and $Y_{i2}$ can be used, and so on until *t*=*T*, the vector of $(Y_{i1}, Y_{i2}, ..., Y_{i,T-2})$ can be used. In other words, the dependent variable of lagged two periods or higher are used as instruments in the first-differenced equation with the following moment conditions:

$$E[Y_{it-s}\Delta v_{it}] = 0 \text{ for } t=3,\ldots,T \text{ and } s \geq 2 \tag{3.23}$$

To improve the efficiency of the estimator, both past and future explanatory variables are also valid instruments if the Xs are strictly exogeneous variables, such that:

$$E[\Delta X_{it-s}\Delta v_{it}] = 0 \text{ for } t=3,\ldots,T \text{ and all } s$$

When $T > 3$ the model is overidentified and the 2SLS is not asymptotically efficient even if the complete set of available instruments is used for each equation and the error terms are homoskedastic. Arellano and Bond (1991) shows that the Generalized Method of Moments (GMM) developed by Hansen (1982) can provide an asymptotically efficient estimator in this content. The GMM estimator uses all the past information of the dependent variable $Y_{it}$ as instruments on the structure of the error term to obtain a consistent GLS estimator. GMM is favoured against OLS estimator because the OLS estimator suffers from several shortcomings; it has a mean reversion tendency, it is inefficient for non-normal distributions and it introduces significant biases when stocks are illiquid. Conversely, the GMM estimator does not rely on the assumptions of normality, homoskedasticity and serial correlation as required by the OLS estimator.

In using the GMM estimator, the issue of reverse causality is crucial. We have to deal with potential endogeneity of both the lagged dependent variable and the determinant variables carefully. If there is endogeneity problem, meaning the explanatory variable, is correlated with the current or past realizations of the error term, such that $E[\Delta X_{it-s}\Delta v_{it}] \neq 0$ for $s \geq t$, and if X is assumed to be weakly exogenous, such that $E[\Delta X_{it-s}\Delta v_{it}] = 0$ for $s < t$, then the instruments available for the first differenced equations are weak (Blundell and Bond, 1998) when $\alpha$ approaches unity and $\sigma_{\eta}^{2}$ increases relative to $\sigma_{\varepsilon}^{2}$.

Blundell and Bond (1998) shows that first-differenced GMM may be subject to a large downward finite-sample bias if the time period is small, making the GMM estimator poorly behaved because the lagged levels of the variables are only weak instruments, especially when the data is highly persistent in a small *T* panel setting. According to Arellano and Bover (1995) and Blundell and Bond (1998), if we assume the variables are mean stationary, then additional moment conditions can be exploited to form a system GMM to alleviate the weak-instrument problem. A simple rule of thumb is to check if $\alpha$ from the first-differenced GMM lies in between those estimated by the pooled estimator and the within estimator. If the GMM $\alpha$ is close to or below the within estimator, it is likely the GMM estimator is also biased downwards due possibly to weak instruments.

### 3.4.4 The System Dynamic Panel Model with GMM Estimators

Following Arellano and Bover (1995) and Blundell and Bond (1998), a system GMM can provide much superior finite sample properties and thus a more efficient estimator. Basically the system GMM makes supplementary moment conditions exist for the equation in level. Consider augmentation on the first-differenced GMM with:

$$E\left[v_{it}\Delta Y_{it-1}\right]=0 \text{ for } t=3,\ldots,T \tag{3.24}$$

This allows the use of lagged first-differences of the series as instruments for the equations in levels.

For strictly exogenous explanatory variables, the appropriate level moment conditions would be:

$$E\left[v_{it}\Delta X_{it-s}\right]=0 \text{ for } t=3,\ldots,T \text{ and all } s \tag{3.25}$$

While for weakly exogenous explanatory variables, the appropriate level moment conditions would be:

$$E\left[v_{it}\Delta X_{it-s}\right]=0 \text{ for } t=3,\ldots,T \text{ and all } s\geq 1 \tag{3.26}$$

The system GMM basically used these assumptions under a stacked system of ($T$-2) equations in both the first-differences and the levels. In other words, the system GMM estimator combines the first-differenced equations with suitably lagged levels as instruments, with an additional set of equations in levels with suitably lagged first differences as instruments. We can then apply a Sargan test to verify if there is any over-identification problem.

### 3.4.5 Specification Tests on Panel Model

A list of specification tests is available to find out which of the panel regression settings is suitable for the dataset employed. From pooled to fixed or random effect, we can rely on F-test and LM test, respectively. To compare fixed or random effect, we can refer to Hausman test. To see if a dynamic specification is suitable, then the first-order and second-order autocorrelation tests are needed. In addition, a Sargan Test can be employed to examine the validity of instrumental variables used in estimators.

***Fixed Effect Model versus Pooled Model: F Test***

In order to decide whether a fixed effect specification is superior to the pooled regression specification, a simple *F* test is conducted. The hypothesis to be tested is:

$H_0$: Pooled regression model

$H_1$: Fixed effect model

The *F* test statistic is given by:

$$F_0 = \frac{(RSS_{Pooled} - RSS_{Fixed})/(N-1)}{(RSS_{Fixed})/(NT - N - k - 1)} \tag{3.27}$$

where $RSS_{Pooled}$ and $RSS_{Fixed}$ are the residual sum of squares for the pooled regression and the fixed effects model, respectively, and $k$ is the number of regressors in the fixed effect model. The *F* statistic is distributed as $F_{N-1, NT-N-k-1}$ under $H_0$. If $F_0$ is significant, the fixed effect model is the preferred model. Alternatively, one can also perform the Chi-square test that is equivalent to the *F* test.

***Random Effect Model versus Pooled Model: Breusch-Pagan LM Test***

The Lagrange multiplier (LM) specification test proposed by Breusch and Pagan (1980) can be used to test for significance of random effects over the pool regression. The null hypothesis for one-way firm random effect is that the firm variance component is zero, with test statistic given as follow:

$$LM_{\eta} = \frac{NT}{2(T-1)}\left(\frac{\sum_{N}\left(\sum_{T}\varepsilon_{it}\right)^{2}}{\sum_{N}\sum_{T}\varepsilon_{it}^{2}} - 1\right)^{2} \sim \chi_{1}^{2} \text{ under } H_0 \tag{3.28}$$

For two-way random effects, the LM test combines both the LM statistics of both firm and period variance components and the null hypothesis is that they are zero as given in the following equation:

$$LM = LM_{\eta} + LM_{\xi} \sim \chi_{2}^{2} \text{ under } H_0$$

***Random Effect Model versus Fixed Effect Model: Hausman Test***

If the null hypothesis is rejected in favour of choosing the fixed effect model, the next step is to verify whether a random effect model is more superior. The specification test proposed by Hausman (1978) is used to test for orthogonality between the random effects and the independent variables. If $E(\varepsilon_{it} | Z_{it}) \neq 0$, the GLS estimator becomes biased and inconsistent.

The Hausman test statistics is given by:

$$H = (\hat{\delta}_{Fixed} - \hat{\delta}_{Random})'[Var(\hat{\delta}_{Fixed}) - Var(\hat{\delta}_{Random})]^{-1}(\hat{\delta}_{Fixed} - \hat{\delta}_{Random}) \tag{3.29}$$

where $\hat{\delta}_{Fixed}$ is the estimator for the fixed effect model, $\hat{\delta}_{Random}$ is the estimator for the random effect model, and $Var$ denotes the variance. The hypothesis to be tested is:

$H_0$: Random effect model

$H_1$: Fixed effect model

For the details of the Hausman test, see Baltagi (2002), Hsiao (2003), and Greene (2003). In fact, when *T* is large, both the fixed effect and GLS estimators should not be significantly different (Hsiao, 2003, p. 41, 51).

***GMM Dynamic Panel Specification: Autocorrelation $m_j$ Test***

For a first order dynamic panel specification where the lagged dependent variable is included as a regressor, if the errors in levels are serially independent, we can expect those in first differences will have first order serial correlation. However, in this case, second or higher order serial correlation should not occur. The $m_j$ statistic proposed by Arellano and Bond (1991) is employed. The autocorrelation $m_j$ test is asymptotically distributed as $N(0, 1)$ under the null of no autocorrelation. It is calculated from residuals in the first difference regression model. If the errors in levels are uncorrelated, we would expect $m_1$ the autocorrelation test of order one to be significant, but not $m_2$ the autocorrelation test for the second order.

In general, the $m_j$ statistics are the moment tests of significance of the average $j$-th order autocovariance $c_j$ given by:

$$c_j = \frac{1}{T-3-j} \sum_{t=4+j}^{T} c_{tj}$$

where $c_j = E\left\lfloor v_{it} \Delta v_{i(t-j)} \right\rfloor$.

The null hypothesis is $H_0$: $c_j = 0$ and the test statistic is given by:

$$m_j = \frac{\hat{c}_j}{SE(\hat{c}_j)} \tag{3.30}$$

where the denominator represents the standard error of the estimated $\hat{c}_j$. See Arellano and Bond (1991) for further detail regarding the test.

***Validity of GMM Instrumental Regression: Sargan Test***

To test whether an instrumental regression is overidentified, we may test the validity of the instruments by checking if the excluded instruments are uncorrelated with the error process. The null hypothesis is all instruments are uncorrelated with the error term. A strong rejection of the null hypothesis implies that the estimates are invalid, or the equation is overidentified.

The Sargan test statistic is given as:

$$S = \hat{\varepsilon}'Z\left(\frac{1}{N}\sum_{i=1}^{N} Z_i'\hat{\varepsilon}\hat{\varepsilon}'Z_i\right)^{-1} Z_i'\hat{\varepsilon} \tag{3.31}$$

Basically $S = nR_{IV}^2$ where $n$ is the number of observations and $R_{IV}^2$ is the $R^2$ obtained from the regression of the residuals saved from the instrumental variable regression on all the exogenous variables, which include both instrumental and the control variables. $S$ is distributed as $\chi_{m-r}^2$ under the null hypothesis where $m$-$r$ is the number of instruments or moment condition minus the number of endogenous variables or the parameters. Under GMM, the statistic will be identically zero for any exactly-identified equation, and will be positive for overidentified equations.

## 3.5 Data and Procedure

### 3.5.1 Data Description

The sample for this study covers the period from 3 January 2001 to 31 December 2008. All data were collected from DataStream, which include the weekly prices of stocks listed on the Main Board of Bursa Malaysia as well as the market indices. The KLCI was used as proxy for Malaysian market index and the MSCI US price index was used as proxy for the global market index.[7] Weekly data were used in the estimation of all

[7] The MSCI US market index is used due to the unavailability of global market risk premiums for the calculation of cost of equity. All data on market risk premiums were collected from Damodaran's website for consistency.

risk measures. Weekly frequency is preferable because daily series has more noise that may affect the quality of the cost of equity estimates.[8] The annual averages of the weekly 3-month Treasury bill rates of Malaysia and the U.S. were used to represent the local and global risk-free rate, respectively. The variables used for exploring the determinants of firm's cost of equity were also obtained from the DataStream database. Annual observations were collected from DataStream that compiles the information from the annual report of each individual firm listed in Bursa Malaysia.

The calculation of cost of equity in equations (3.2), (3.3) (3.4), (3.5), (3.6), (3.7) (3.8) and (3.9) involves the expected value or ex-ante local and global market risk premiums. However, as different researchers used different approach and assumption in risk premium calculation, there is no consensus on the value of these ex-ante local and global market risk premiums (Fernández, 2009). We decided to adopt the approach and estimates provided by Damodaran (http://pages.stern.nyu.edu/~adamodar/) as they are most widely used in the industry thus far (Fernández, 2009). In the estimation of the long-term country risk premium, Damodaran started by referring to the country ratings by Moody's (www.moodys.com). A default spread for a country is computed by comparing the country's dollar-denominated bond[9] with the U.S. Treasury bond rate. This default rate becomes a measure of added country risk premium for that country and is then multiplied with a global average of equity to bond market volatility of 1.5 to obtain the country equity risk premium. The total (market) risk premium for a country is obtained by adding the country equity risk premium to the historical risk premium of a mature market, in this case, the U.S. market.

[8] For the weekly series, Wednesday closing prices were collected to avoid the Monday and Friday effects.
[9] Bonds denominated in other currencies such as the Euro or Yen can also be used as long as there is a risk-free rate (from a mature market) for comparison.

Following Damodaran (2010), the sovereign bond premium approach was used to overcome the problem associated with the estimation of market risk premium for emerging markets. Accordingly, the Malaysian equity risk premium was computed as the sum of the premium of a developed market (that is, the U.S. for this study) and Malaysia's country risk premium, which is available from Damodaran's website on annual basis from year 2001 to 2008. Since global market risk premium is not available, the U.S. market risk premium was taken as the proxy. Given that only annual risk premiums are available, the costs of equity were calculated on annual basis.

We included firms from seven sectors of the Main Board in Bursa Malaysia. After filtering out new firms which were listed after 2001 because they do not have a complete series of data for the full sample period, we have a total of 354 firms available for analysis. They are from Construction (28 firms), Consumer Products (54 firms), Industrial Products (129 firms), Plantation (21 firms), Properties (33 firms), Technology (12 firms) and Trading/Services (77 firms). Finance sector is excluded from the study because not all firm ratios will apply similarly to financial institutions. For example, a bank's strength is not gauged so much by its cash flow and debt-to-equity ratio but its tier 1 capital ratio[10] and loan-to-deposit ratio. Mining is also excluded because only two firms passed the filtering process.

### 3.5.2 Cost of Equity Measurement

The risk measure for each firm was estimated using weekly data based on regression models (3.2a), (3.3a) (3.4a), (3.5a), (3.6a) and (3.7a). The estimates were obtained for every year in the sample period. The total risk and the semi standard deviation were calculated based on equations (3.8a) and (3.9a). After obtaining the annual risk

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[10] Tier 1 capital ratio is the core measure of a bank's strength from the viewpoint of a regulator. In layman's term, it is a measure of the bank's sustainability to future losses. For example, a 10% tier 1 capital measure means that for every RM10 deposited by customer, the bank is holding RM1 in its vaults or likewise locations.

measures for 2001 to 2008, we calculated the cost of equity of the firms following models (3.2), (3.3) (3.4), (3.5), (3.6), (3.7) (3.8) and (3.9) by employing the various annual risk free rates and annual risk premiums provided by Damodaran (http://pages.stern.nyu.edu/~adamodar/).

With 354 sample firms, eight years of sample period and eight variations of cost of equity measures, where two variations are from the two-factor models with two risk measures each, we calculated a total of: (354 firms) x (8 years) x (10 risk measures) = 28,320 observations of annual risk measures. A total of: (354 firms) x (10 risk measures) = 3,540 series of firm level risk measures were obtained.

For model selection purposes, the 3,540 calculated annual firm risk series were stacked into ten pooled risk series for the regression with the stacked series of firms' actual returns (ex-post) according to equation (3.10). The adjusted $R^2$ of the models were recorded and used as the selection criterion to find out which of the risk measures has the highest explanatory power to be used subsequently for the panel regression analysis of the determinants of cost of equity.

### 3.5.3 Cost of Equity Determinants

For each variable that is to be used in the panel determinant regression, the eight-year time series (2001-2008) for the 354 firms were stacked to construct pooled series. For the full sample, each of the pooled series contains 354 firms x 8 years = 2,832 observations. A similar procedure was used to stack the dependent variable, that is, the pooled cost of equity series.

Besides conducting panel regression analysis for the full sample, we also conduct the same analysis for all the seven sub-sectors. So we need to reconstruct a different set of pooled series. The length of the pooled series for each sector depends on the number of firms available. The following are the number of observations for the pooled series of each of the seven sectors for the panel regression analysis over 2001-2008:

1. Construction: 28 firms x 8 years = 224 observations
2. Consumer Products: 54 firms x 8 years = 432 observations
3. Industrial Products: 129 firms x 8 years = 1032 observations
4. Plantation: 21 firms x 8 years = 168 observations
5. Properties: 33 firms x 8 years = 264 observations
6. Technology: 12 firms x 8 years = 96 observations
7. Trading/Services: 77 firms x 8 years = 616 observations

All these pooled series were used for panel regression of both the static and dynamic models. There are three settings for the static panel model, that is, pooled model, fixed effect model, and random effect model. There are two settings for the dynamic panel regression, that is, GMM model and system GMM model. With eight sets of panel to be estimated, that is, for the full sample and for the seven sub-sectors, a total of 40 panel regression models were produced.

Finally, after obtaining the results, the full sample estimates were compared with the estimates for the seven sub-sectors to examine the sectoral effects of the cost of equity determinants. The estimates produced at the sectoral level can also serve as a robustness check for the full sample panel estimates. If the coefficient of a determinant variable is statistically significant for more than two sub-sectors with the condition it is also statistically significant for the full sample, it can be concluded that the variable is an important determinant of the cost of equity of Malaysian firms.