Three Essays on Empirical Finance

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To my parents for their unconditional love and support

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CHAPTER I

DEBT-EQUITY SUBSTITUTION, GROWTH OPTIONS AND MARKET TIMING

1. Introduction

A large number of studies find that corporate financing activities predict future stock returns. For capital raising activities, firms are found to underperform their stock return benchmarks after initial public offerings (Ritter (1991)), seasoned equity offerings (Loughran and Ritter (1995)), public debt offerings (Spiess and Affleck-Garves (1999)) and bank borrowings (Billett, Flannery and Garfinkel (2001)). For capital distribution activities, previous studies find firms earn abnormally high stock returns after stock repurchases (Ikenberry, Lankonishok and Vermaelen (1995)). A recent study by Bradshaw, Richardson and Sloan (2006) examines the commonalities among various financing anomalies. Using the statement of cash flows data, they develop a comprehensive measure of corporate financing activities. They show that the net amount of cash generated by corporate financing activities is a more powerful predictor of future stock returns than individual categories of financing activities. They thus suggest that the various financing anomalies are part of a broader net financing effect.

There has been much debate about whether financing anomalies are consistent with the mispricing hypothesis or with the efficient market hypothesis. From the mispricing perspective, financing anomalies occur because firms tend to issue new securities when they are overvalued (Bradshaw, Richarson and Sloan (2006), Loughran and Ritter (1996), Ritter (1991)). Issuers earn lower returns when mispricing is corrected in subsequent periods. Supporters of the efficient market perspective argue that the lower stock returns earned by issuers reflect investors' rational expectations. A particular strand of the efficient market explanation argues that equity and debt issuers earn lower average returns because they use the proceeds to finance new investment (Li, Livdan and Zhang (2009), Liu, Whited and Zhang (2009) and Lyandres, Sun and Zhang (2007)). These authors argue that the negative relation between external financing and future stock return simply reflects the negative relation between investment and expected return. They base their argument on either the q-theory of investment (Cochrane (1991)) or the real options theory (Carlson, Fisher and Giammarino (2004)). According to the q-theory of investment, firms invest more when marginal q is higher and marginal q is higher when the discount rate is lower. According to the real options theory, investment converts risky growth options into real assets. Since real assets are less risky than growth options, firms' required rates of return decrease after investment. Therefore, both the q-theory of investment and the real options theory imply a negative relation between real investment and future stock returns.

Several recent studies find empirical evidence in support of the investment based theories. In one of the studies, Lyandres, Sun and Zhang (2007) show that an investment factor, long in low-investment stocks and short in high-investment stocks, helps explain the new issues puzzle. While their findings are consistent with the investment based theories, it is not clear whether mispricing plays a role in driving the negative relation between investment and future stock returns[1]. In another study, Butler, Cornaggia, Grullon and Weston (hereafter referred to as BCGW (2010)) more explicitly test the mispricing hypothesis against the investment based theories through a debt-equity substitution hypothesis. They argue that market timers should strategically substitute equity for debt when they expect low future stock returns. Consequently, equity issuers should earn lower future stock returns than debt issuers if the market timing hypothesis holds. However, they find that future stock return is negatively related only to the level of external financing, but not to the debt-equity composition of external financing. They thus conclude that the data do not support the mispricing hypothesis. In addition to this firm level

[1] For example, Titman, Wei and Xie (2004) argue that investors misprice firms that substantially increase capital investments because they do not fully anticipate the empire building implications of increased investment expenditures. It is also possible that market mispricing simultaneously affects firms' financing and investment decisions. For example, Shleifer and Vishny (2003) suggest that, when firms' stocks are overvalued, managers are more likely to make stock financed acquisitions. It can even be argued that firms may pursue additional investment projects simply because they need an excuse for issuing more securities at favorable prices.

study, several other papers have examined whether firms' debt-equity issuance choices predict aggregate stock market returns (Baker and Wurgler (2000), Baker , Taliaffrro and Wurgler (2006), Butler, Grullon, and Weston (2005), Welch and Goyal (2007), etc).

A potential concern over these studies is that they do not control for the risk characteristics of new investments. Supporters for the investment-based explanations tend to assume that firms use the proceeds from external financing activities to invest in real assets, neglecting the possibility that they can also use the proceeds to develop more growth options. Firms become riskier when their growth options increase relative to their real asset bases. Investors will require higher rates of returns for holding the equities of these firms. Moreover, capital structure studies suggest that firms are more likely to use equity than debt to finance new growth options[2]. Therefore, when firms indeed invest in new growth options, there can be a positive correlation between equity financing and future stock return, exactly the opposite to what the market timing theory suggests. If the market timing time effect and the confounding investment-in-growth-options effect both exist in the data, one effect cannot be easily detected without controlling for the other.

In this paper, we consider threes alternative procedures for testing the debt-equity substitution hypothesis. First, we investigate whether investors are more negatively surprised by equity issuers than by debt issuers at subsequent earnings announcements. Second, we examine the relation between firms' debt-equity choices and year-ahead stock returns after controlling for the investment-in-growth-options effect. Third, we examine whether analysts' forecasts of long term growth rates are more overoptimistic for heavy equity issuers than for heavy debt issuers. We find that the results from all three tests support the mispricing hypothesis.

[2] Equity financing is the preferred method for developing new growth options due to concerns over collateral value, underinvestment costs (Myers (1977)) and agency costs of free cash flow (Jensen (1986)). Hovokimian, Opler and Titman (2001) suggest that 'firms should use relatively more debt to finance assets in place and relatively more equity to finance growth opportunities''. Barclay, Smith and Morellac (2006) further show that, if debt capacity is defined as the incremental debt optimally associated with an additional asset, the debt capacity of growth options is negative.

The earnings announcement test is our main testing procedure. From the mispricing perspective, more overvalued firms will issue more equity relative to debt to exploit market mispricing. Consequently, investors will be more negatively surprised by heavy equity issuers than by heavy debt issuers at subsequent earnings announcements. Therefore, if the mispricing hypothesis holds, firms issuing more equity relative to debt should earn lower event returns at subsequent earnings announcements than those issuing more debt relative to equity. The investment based theories makes no such predictions. According to the investment based theories, investors are surprised by neither the equity issuers nor the debt issuers. They provide no clear reason why investors will be more negatively surprised by heavy equity issuers than by heavy debt issuers. We focus on earnings announcement returns to enhance the statistical power of our tests. Realized stock returns reflect both investors' expectations and surprises to investors. Several authors argue that the surprises to investor tend to cluster around earnings announcements, while the expected components should be distributed more smoothly over the year (e.g., Sloan (1996), La Porta, Lakonishok, Shleifer and Vishny (1997), Titman, Wei and Xie (2004), Cooper, Gullen, Schill (2008))[3]. Since market mispricing is closely related to the surprises to investors, the earnings announcement test is potentially a more powerful test for the market timing hypothesis, especially for situations where confounding effects may exist in expected returns.

Several previous studies have examined earnings announcement returns in search for evidence of mispricing. For example, La Porta, Lakonishok, Shleifer and Vishny (1997) use this method to examine whether the value premium can be attributed to the expectational errors made by investors. More relevant to financing anomalies, several other studies find evidence of significantly negative stock price reactions to earnings announcements after equity issues (Rangan (1998) and Jegadeesh (1998)). Notice that negative stock price reactions to earnings announcements, by themselves, are not sufficient to prove the mispricing hypothesis because

3 We use this argument only for explaining why the earnings announcement test has more statistical power for testing the mispricing hypothesis. For reasons that we will explain shortly afterwards, we do not use the concentration of stock return effects at earnings announcements as the criterion for identifying anomalies.

there is also an expected return component in earnings announcement returns[4]. These studies generally base their statistical inferences on the "concentration argument". That is, they argue that stock return effects that are highly concentrated at earnings announcements are likely to be anomalies. However, it is not clear what the threshold concentration level should be for indentifying anomalies. Moreover, Wu, Zhang and Zhang (2009) show that stock return is identical to return on assets in their q theory based model. They thus argue that, in their model, it is natural for expected return to be realized around earnings announcements when earnings news is released to the market. Therefore, the traditional "concentration argument" may not work when one of the alternative hypotheses is related the q-theory of investment. Our statistical inference does not rely on the "concentration argument". By focusing on firms' debt-equity choices, we form testable hypothesis for separating the market timing story from investment based theories. In this sense, our test specification will provide more reliable evidence regarding financing anomalies than previous earnings announcement studies do.

We start our earnings announcement tests from a two way sort of raw and benchmark-adjusted earnings announcement returns (EARs) by the level and debt-equity composition of external financing. Following BCGW (2010), we use equity ratio as the proxy for firms' debt-equity choices. Equity ratio is defined as the proportion of equity in the net amount of cash raised (distributed) during the year. Capital raising (distributing) firms with higher equity ratios issue (repurchase) more equity relative to debt. For each year, we sort capital raising (distributing) firms into portfolios first by net external financing (NF) and then by equity ratio (ER). We then examine how the EARs vary across the NF × ER portfolios. We find capital raising firms with higher ER (i.e., firms issuing more equity relative to debt) earn lower returns at the subsequent earnings announcements. As discussed earlier, this is consistent with the mispricing hypothesis. The negative relation between EARs and ER is confirmed by cross-sectional regression results.

[4] Firm characteristics that are often viewed as capturing risks, such as size, book-to-market ratio and momentum, are also significantly negatively related to earnings announcement returns.

The regression coefficients indicate that, controlling for the level of net external financing, size, book-to-market ratio, momentum, asset growth (investment) and ROA, a hedge portfolio formed by shorting the capital-raising firms in the highest ER decile and longing those in the lowest ER decile generate 1.64% in abnormal return over the subsequent four earnings announcements. In comparison, a hedge portfolio formed by longing and shorting extreme book-to-market ratio deciles generates 1.50% in abnormal return over the four earnings announcements. This comparison shows that earnings announcement effects associated with firms' debt-equity choices are of similar economic magnitude as the well-known book-to-market effect. These results suggest that heavy equity issuers have significantly lower earnings announcement returns than heavy debt issuers.

Our earnings announcement test results suggest that investors are systematically more negatively surprised by heavy equity issuers than by heavy debt issuers. This is consistent with the mispricing hypothesis, but in inconsistent with BCGW's (2010) findings. To reconcile our earnings announcement test results with the findings by BCGW (2010), we examine the relation between year-ahead stock returns and equity ratios, with and without controlling for the investment-in-growth-options effect. If our conjectures about the market timing effect and the investment-in-growth-options effect hold, we expect to obtain different results before and after controlling for the investment-in-growth-options effect. We sort firms into portfolios first by NF and then by ER and examine how the raw and benchmark-adjusted 12-month buy-and-hold returns (BHARs) vary across the NF×ER portfolios. The benchmark-adjusted BHARs are defined as raw BHARs minus the mean BHARs of firms with similar size, book-to-market ratio and momentum. Consistent with BCGW (2010), we find no difference in benchmark-adjusted BHARs across the equity ratio portfolios before controlling for the investment-in-growth-options effect. To control for the investment-in-growth-options effect, we use R&D expenditures as the proxy for firms' propensities to invest in growth options. It should be emphasized that R&D spending, intuitive as it is, is only a partial control for investment-in-growth-options effect because not all growth options are R&D related. In this sense, the evidence in this paper only provides very conservative estimates of the abnormal returns associated with firms' debt-equity choices. However, our objective is not to obtain precise point estimates of the abnormal returns associated with firms' debt-equity choices, but to verify whether different conclusions about the mispricing hypothesis can be reached before and after including a partial control for the investment in growth options. We examine how the BHARs vary by NF and ER after excluding from the portfolios firms with R&D expenditures higher than 5% of lagged assets. These high R&D firms are firms among which the investment-in-growth-options effect is likely to be the strongest. Once these firms are excluded from the sample, we find the raw and benchmark-adjusted BHARs differ between the ER portfolios in the way predicted by the mispricing hypothesis. We obtain similar results from cross-sectional regressions. Without controlling for the investment-in-growth-options effect, the regression results suggest there is no relation between equity ratio and future stock return. However, once we include R&D as a control variable, the relation between equity ratio and future stock return is reliably negative for the capital raising firms. The effect is robust to the inclusion of various control variables, such as the level of net external financing, size, book-to-market, momentum, asset growth and ROA. Therefore, after controlling for the investment-in-growth-options effect, both the portfolio sorts analysis and cross-sectional regression analysis detect evidence for the mispricing hypothesis.

In our analysis, we find R&D expenditure is significantly positively related to year-ahead stock returns. On average, high R&D firms earn 8.55% more per annum than low R&D firms. However, R&D expenditure is not significantly related to earnings announcement returns. Following the argument in previous earnings announcement studies (e.g., Sloan (1996) and La Portfa, Lakonishok, Shleifer and Vishny (1997)), these results suggest that the higher year-ahead returns on R&D are more likely to be the rationally expected components of stock returns than the surprises to investors. This is consistent with the view that investors require higher returns for holding the equities of high R&D firms (Berk, Green and Naik (2004) and Li (forthcoming)).

More importantly, these findings suggest that the market timing effect, relative to the investment-in-growth-options effect, is stronger on the earnings announcement days than during other times of the year. This explains why the earnings announcement test can detect evidence for market timing without controlling for R&D.

In search for further evidence of mispricing, we examine the relation between equity ratio and analysts' forecasts of firms' long term growth rates. Previous research suggests that expectational errors in long term growth rates play an important role in stock market predictability (e.g., Dechow and Sloan (1997) and La Porta (1996)). Since the results from both the earnings announcement test and the year-ahead stock return test support the mispricing hypothesis, we expect that analysts make more overoptimistic forecasts about heavy equity issuers' growth prospects than about heavy debt issuers' growth prospects. We find evidence consistent with our expectations. While analysts are overoptimistic about both heavy equity issuers and heavy debt issuers, they overestimate the growth prospects of the former more than they overestimate the growth prospects of the latter by 4.84% to 10.76% per annum.

Putting together, our results suggest that two opposite relations exist between firms' debt-equity choices and future stock returns. Because of managerial market timing, equity financing is more negatively related to future *abnormal returns* than debt financing is. At the same time, there can be a positive correlation between equity financing and *expected returns* when firms use equity as the preferred method for financing growth options. Previous studies generally neglect the latter effect. This could be one of the reasons why they reach conflicting conclusions about equity market timing. For example, Baker and Wurgler (2000) find that equity share in new issues, an aggregate market timing variable similar to the equity ratio used in this paper, has predictive power for future stock market returns. BCGW (2010) find that Baker and Wurgler's (2006) results no longer hold after adding years after 1997 into the sample. Our descriptive statistics show that the proportion of high R&D firms (i.e., firms among which the confounding effect is the strongest) in our sample increase over the years. As the number of high R&D firms increase, the investment-in-growth-options effect strengthens at the aggregate level and eventually completely offsets the market timing effect in the data.

Knowing that the mispricing effect exists beyond the investment-based theories also has important implications for capital structure studies. A large number of capital structure studies report evidence of market timing in firms' debt-equity choices and/or examine whether firms undo previous market timing activities (Baker and Wurgler (2005), Alti (2006), Leary and Roberts (2005), Kayhan and Titman (2007)). In their survey on capital structure studies, Frank and Goyal (2007) suggest that the issue is not whether market conditions affect leverage decisions, but how persistent the market timing effects are. If the market timing effect does not survive the investment based theories, there will be no need to study the persistence of the market timing effects. Our findings provide reassuring evidence about equity market timing.

The rest of the paper proceeds as follows. Section 2 discusses the data and descriptive statistics. Section 3 discusses the results of the earnings announcement tests. Section 4 presents the evidence regarding the relation between debt-equity composition, growth options and year-ahead stock returns. Section 5 examines the relation between debt-equity composition and analysts' forecasts of firms' long term growth rates. Section 6 explains how the new growth options effect can explain the controversy about aggregate market timing. Section 7 concludes.

2. Data

We obtain stock return data from CRSP and accounting data from Compustat. Our initial sample includes all non-financial firms that are listed on NYSE, Nasdaq or Amex at the end of each June from 1972 to 2009. ARDs, REITs, closed-end funds, and other stocks that do not have a CRSP share type code of 10 or 11 are excluded from the sample. We follow the standard practice of matching the firm-year observations for June of calendar year t with the accounting information for the fiscal year ending in calendar year t – 1. To mitigate backfilling biases, we require that a firm be listed on Compustat for two years before including it in the dataset (Fama and French (1993)). Since our goal is to test the debt-equity substitution hypothesis, we require that sample firms have Compustat data available for calculating the external financing variables.

Following Bradshaw, Richardson and Sloan (2006), we use net external financing (NF) as a comprehensive measure of the firms' financing activities. The net external financing variable is calculated as

$$NF_t = Net\ equity\ issue_t\ + Net\ debt\ issue_t \quad (1)$$

Net equity issue is the net amount of cash from issuing and repurchasing equities (SSTK-PRSTKC) during the year. Net debt issue is the net amount of cash from issuing and repurchasing debt securities (DLTIS - DLTR) during the year[5]. The net external financing, net equity issue and net debt issue variables are scaled by average total assets. Following BCGW (2010), we calculate equity ratio (ER) as

$$ER_t = Netequity\ issue_t/(Net\ equity\ issue_t + Net\ debt\ issue_t) \quad (2)$$

Capital raising (distributing) firms with higher equity ratio issue (repurchase) more equity relative to debt. This variable can thus be used as a proxy for firms' equity market timing activities. One potential concern over the equity ratio variable is that it can be a noisy measure for market timing incentives when firms issue only a small amount of debt or equity. For example, a firm can have an equity ratio of 100% if it issues no debt and its employees exercise a small number of options. Similarly, it can have an equity ratio of 0 if it issues no equity but a small amount of debt to finance its routine operations. In neither case does the ratio reflect managers' incentives to time the market. For this reason, we impose an additional requirement that sample firms issue (repurchase) debt or equity that amounts to at least 1% of their lagged assets. By so doing, we exclude the observations with potentially the noisiest equity ratios. Moreover, when the issue size is large, managers are likely to pay more attention to whether the firms are under- or over-valued

[5] Following Bradshaw, Richardson and Sloan (2006), we set change in current debt (DLTR) to 0 if the variable has a missing value in the Compustat database.

by the market in making their debt-equity choices. In this sense, this additional requirement enhances the power of our test for detecting market timing activities. The resulting sample consists of 93,922 observations over the 38 years between 1972 and 2009.

Another concern over the equity ratio is that it may not have a one-to-one relation with future stock returns. Suppose two issuers have the same equity ratio of, say, 25%. The issue size as a percentage of asset base is 1% for one firm and 20% for another. It is unlikely the same equity ratio has the same effect on the future stock returns of the two firms. The economic magnitude of stock return effects associated with the equity ratio, if any, is likely to be much larger for the relatively larger issue. To address this concern, we use the rank of the equity ratio in regressions. Following Mashruwalaa, Rajgopala, and Shevli (2006), we rank firms into deciles each year by their equity ratio and then transform the decile rankings to a value between -0.5 and 0.5 (hereafter referred to as ER^{dec}).[6] The major conclusions do not change when percentile rankings are used. The decile ranking takes the value of 0.5 when a firm is in the highest equity ratio decile and -0.5 when a firm is in the lowest equity ratio decile. When stock returns are regressed on this variable, the coefficient can be interpreted as the return on a hedge portfolio formed by longing the firms in the highest equity ratio decile and shorting those in the lowest equity ratio decile.

For each firm-year observation at the June of year t, we calculate its 12-month buy-and-hold stock return (BHAR) from July of year t to June of year t + 1. Following the procedures used by Daniel, Grinblatt, Titman and Wermers (1997) and Baker, Litov, Wachter and Wurgler (2010), we form benchmark groups for our sample firms based on size, book-to-market (BM) and

[6] We transform the ER decile ranking to a value between -0.5 and 0.5 rather than to a value between 0 and 1 because we use the interaction terms between POSNF (NEGNF) and ER decile ranking in our regressions. POSNF and NEGNF are indicator variables that take the value of one for firms with positive (negative) net external financing and 0 otherwise. If we transform equity ratio decile to a value between 0 and 1, the coefficients for the interaction terms will be difficult to interpret in some situations. For examples, the interaction term between POSNF and ER decile ranking will be 0 for three types of firms: firms with ER decile ranking of 0 and POSNF of 0, firms with ER decile ranking of 1 and POSNF of 0 and firms with ER decile ranking of 0 and POSNF of 1. This will reduce the statistical power of our tests.

momentum (MOM).[7] If a stock is delisted during the 12 month period, we invest the delisting proceeds evenly into other stocks in the same size × BM × MOM group. We use both raw and benchmark-adjusted BHARs in our portfolio sort analysis. The benchmark-adjusted BHAR is calculated as the raw BHAR minus the average BHAR of a size × BM × MOM benchmark group.

For earnings announcement tests, we match each firm-year observation at the June of year t to the earnings announcements that occur between July of year t and June of year t + 1 and then calculate the three day buy-and-hold earnings announcement return (EAR) for each event. Again, we use both raw and benchmark-adjusted EARs in our portfolio sort analysis. The benchmark-adjusted EAR is defined as the raw EAR minus the average EAR for stocks of similar size, book-to-market ratio and momentum that announce earnings in the same calendar quarter. Ideally, each sample firm will be matched to four earnings announcements during the 12 month period. However, for several reasons, some of the firm-year observations are matched to more or less than four earnings announcements. First, due to fiscal year change, one earning announcement date may correspond to different fiscal periods for some of the stocks. We exclude these duplicate observations from the sample. Second, some firms may announce first quarter (fourth quarter) earnings announcements earlier (later) than other firms typically do. In this case, a sample firm may have more than one earnings announcements in a particular calendar quarter. Counting the same firm twice may not be desirable for analyzing earnings announcement effect or for calculating benchmark EARs. We handle the situation by keeping only the first earnings announcement for any particular quarter. Third, for about two hundred earnings announcements, stocks are delisted during the earnings announcement window. We account for delisting returns in calculating EARs. In addition, if a stock is delisted on the announcement day, we use the average

[7] Each June, we sort all NYSE firms into quintiles by size. Then we divide each of the size portfolios into quintiles by book-to-market ratio (BM). Then we divide each of the size × BM portfolios into quintiles by momentum (MOM). Size is defined as the market value of equity at the end of June in year t. BM is defined the book equity as of fiscal year end that occurs in year t – 1 scaled by the market value of equity at the end of December in year t – 1. Mom is defined as the stock return from July of year t – 1 to May of year t. Using these NYSE breakpoints, we divide all NYSE, Nasdaq and Amex stocks into 125 size × BM × MOM benchmark groups.

third day return for stocks of similar size, book-to-market ratio and momentum that announce earnings in the same calendar quarter as the stock return for day D + 1.

In our analysis, we also examine the relation between equity ratio and market expectations of firms' long term EPS growth rates. We use the mean analysts' forecasts of long term EPS growth rates (LTG) from the summary statistics file of the I/B/E/S database as the proxy for consensus forecasts. A large number of studies find that analysts' forecasts are systemically biased upward. Moreover, Dechow and Sloan (1997) find that analysts' forecasts of long term EPS growth are more opportunistic for firms with lower book-to-market or earnings-to-price ratios. We thus calculate benchmark-adjusted LTG for portfolio sort analysis. Again, the benchmark-adjusted LTG is defined as raw LTG minus the average LTG of firms with similar size, book-to-market ratio and momentum.

In Table 1.1, we present the descriptive statistics for the sample firms. For the entire sample, the net external financing (NF) variable has a mean of 0.0686 and a median of 0.0178. In comparison, BCGW (2010) report a mean of 0.06 and a median of 0.01. Our numbers are slightly higher, probably because we impose the additional requirement that that sample firms issue (repurchase) debt or equity securities that amounts to at least 1% of lagged assets. The statistics for the equity ratio (ER) variable cannot be directly compared across studies: BCGW winsorize the variable at 0 and 1 while we winsorize the variable at 1% and 99%. Based on the distribution of the variable in our sample, about 36% of the observations lie outside the 0 - 1 boundary. Table 1.1 also presents the descriptive statistics for several other variables that are used in our analysis. MV is the market value of equity (in thousands of dollars) at the end of June in year t. BM is the book-to-market ratio, defined as the book value of equity as of the fiscal year end that occurs in calendar year t -1 scaled by the market value of equity at the end of December of calendar year t – 1. MOM is the stock return momentum, defined as the 11 month buy-and-hold return from the July of year t – 1 to May of year t. Growth is the change in total assets scaled by lagged assets. ROA is operating income before depreciation scaled by lagged book assets. R&D is research and

Table 1.1. Descriptive statistics

This table presents the descriptive statistics for the sample firms. The sample firms consist of all non-financial firms that are listed on NYSE, Nasdaq or Amex at the end of June each year from 1972 to 2009. NF is net external financing, defined as the net amount of cash from issuing and repurchasing debt and equity securities scaled by average assets. ER is equity ratio, defined as the proportion of net equity to net cash raised. MV is the market value of equity at the end of June in year t. BM is book-to-market ratio, defined as the book value of equity as of the fiscal year ending in calendar year t -1 scaled by the market value of equity at the end of calendar year t – 1. MOM is the 11 month buy-and-hold return from the July of year t – 1 to May of year t. Growth is the change in total assets scaled by lagged assets. ROA is operating income before depreciation scaled by lagged book assets. R&D is research and development spending scaled by lagged assets. We set missing R&D values to zero. BHAR is the 12 month buy-and-hold stock return from July of year t to June of year t + 1. LTG is the mean analysts' forecast of long term EPS growth rate available in June of year t. Except for BHAR, all variables are winsorized at 1% and 99%. Panel A presents the descriptive statistics for the whole sample, Panel B for firm-year observations with positive net external financing and Panel C for firm-year observations with negative external financing.

Panel A: Whole sample

	N	Median	Mean	Std
NF	93,922	0.0178	0.0686	0.2018
ER	93,922	0.0361	0.3314	1.0692
MV	93,922	83,145	971,084	3,103,698
BM	93,922	0.5993	0.8166	0.7990
MOM	93,922	0.0325	0.1198	0.5624
Growth	93,922	0.0900	0.1850	0.4342
ROA	93,803	0.1384	0.1143	0.2059
R&D	93,922	0.0000	0.0401	0.0877
BHAR	93,922	0.0520	0.1512	0.7256
LTG	39,766	15.00%	17.13%	8.98%

Panel B: Capital raising firms vs capital distributing firms

	NF < 0				NF < 0			
	N	Median	Mean	Std	N	Median	Mean	Std
NF	53,948	0.0777	0.1622	0.2186	39,974	-0.0368	-0.0578	0.0583
ER	53,948	0.0978	0.4329	1.0312	39,974	0.0000	0.1945	1.1037
MV	53,948	90,312	799,380	2,603,191	39,974	72,083	1,202,812	3,659,860
BM	53,948	0.5401	0.7348	0.7376	39,974	0.6871	0.9269	0.8629
MOM	53,948	0.0024	0.0911	0.5725	39,974	0.0671	0.1585	0.5461
Growth	53,948	0.1715	0.3048	0.5055	39,974	0.0160	0.0234	0.2293
ROA	53,875	0.1379	0.0947	0.2450	39,928	0.1390	0.1406	0.1319
R&D	53,948	0.0000	0.0513	0.1050	39,974	0.0000	0.0249	0.0530
BHAR	53,948	0.0196	0.1175	0.7346	39,974	0.0911	0.1966	0.7107
LTG	23,019	17.00%	18.73%	9.89%	16,747	13.97%	14.94%	6.99%

development spending scaled by lagged assets.[8] BHAR is the 12 month buy-and-hold stock return from July of year t to June of year t + 1. LTG is the mean analysts' forecast of long term EPS growth rate available in June of year t. This variable is available for only 39,766 firm-year observations. For one thing, I/B/E/S does not provide analysts' forecasts of long term EPS growth rate before 1981. For another, even after 1981, analysts do not provide long term forecasts for all sample firms. Except for BHAR, all variables in Table 1.1 are winsorized at 1% and 99%.

In Panels B and C of Table 1.1, we report the descriptive statistics separately for firms raising capital (NF>0) and for those distributing capital (NF<0). Consistent with the statistics reported by BCGW (2010), firms raising capital are smaller, have lower book-to-market ratios and more aggressive asset growth. More importantly, the distribution of the NF variable is different between the two subsamples. For firms raising capital, the NF variable has a mean of 0.1622 and a standard deviation of 0.2186. For firms distributing capital, the NF variable has a mean of -0.0578 and a standard deviation of 0.0583. Therefore, there is more cross-sectional variation in NF among firms raising capital than among firms distributing capital. This is one of the reasons why BCGW (2010) suggest that the net financing effect may be non-linear in that there may be a larger difference in future stock return for firms raising capital than for firms distributing capital.

3. Equity ratio and earnings announcement returns

3.1. Results from portfolio sorts

In this section, we examine whether the debt-equity composition of net external financing are related to the earnings announcement returns in the subsequent year. At the end of June of

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[8] Following the common practice in previous research, we set missing R&D spending to zero. Huang and Ritter (2009) find that the vast majority of firms with missing R&D are firms in industries such as clothing retailers for which R&D expenditures are likely to be zero. In our regression analysis, we perform robustness checks to ensure that our results are not driven by the assumption that firms with missing R&D values spend negligible amount on research and development.
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each year t, we sort firms into quartiles by net external financing (NF). Then we divide each NF quartile into four portfolios based on the values of the firms' equity ratios.[9] We examine whether the 3-day event returns for the earnings announcements that occur between July of year t and June of year t + 1 differ across the NF × ER portfolios.

For each calendar quarter between July 1972 and June 2010, we calculate equal weighted earnings announcement returns, raw and benchmark-adjusted, for the NF×ER portfolios. We annualize these portfolio level EARs (multiplying by 4) and present the time series means for each portfolio in Table 1.2. In addition, we form low-minus-high hedge portfolios by longing firms in the lowest NF (ER) groups and shorting those in the highest NF (ER) groups. The time series means of the EARs on these hedge portfolios are also presented in Table 1.2. The statistical significance is calculated based on the time series standard errors of the hedge portfolio returns.

We examine firms raising capital and those distributing capital separately. Panel A presents the results calculated using raw EARs for firms raising capital (NF > 0). Consistent with Bradshaw, Richardson and Sloan (2006), the raw announcement period returns decrease from the lowest NF quartiles to the highest NF quartiles. More importantly, for each of the net financing quartiles, the raw EARs decrease from the lowest equity ratio quartile to the highest equity ratio quartile with reasonable degree of monotonicity. The returns on all low-minus-high hedge portfolios are positive and significant at 1% significance level. For example, within the highest NF quartile, firms with the lowest equity ratios earn 2.54% more than those with the highest equity ratios over the four earnings announcements. The evidence in Panel A suggests that both the level of external financing and the debt-equity composition of external financing are related to future earnings announcement returns. Holding the level of external financing constant, firms issuing more equity relative to debt tend to have lower earnings announcement returns than those

[9] If firms' equity ratios are clustered at certain values, such as 0, for a particular NF quartile in a particular year, the number of stocks in each ER portfolio need not be even for that particular NF quartile in that particular year. We sort firms into ER portfolios using the SAS proc rank procedure.

Table 1.2. Earning announcement Returns by NF and ER quartiles

This table reports the annualized earnings announcement returns (%) by net external financing (NF) and equity ratio (ER) quartiles. At the end of June of each year t, we sort firms into quartiles by NF. Then we divide each NF portfolio into quartiles by ER. The NF-ER portfolios are then matched with the earnings announcements that occur between July of year t and June of year t + 1. For each calendar quarter, we calculate the average earnings announcement return (EAR) for each NF-ER portfolio. The annualized (multiplying by 4) returns presented in the table are averages over all formation periods. For each quarter, we also form hedge portfolios by longing stocks in the lowest NF (ER) quartiles and shorting stocks in the highest NF (ER) quartiles. The time series standard errors of the hedge portfolio returns are used to calculate the t-statistics in the parentheses. Panel A presents the raw EARs for capital raising firms (NF >0). The raw EARs are defined as the 3-day buy-and-hold returns surrounding the earnings announcements. Panel B presents the benchmark-adjusted EARs for capital raising firms (NF > 0). The benchmark-adjusted EARs are defined as raw EARs minus the average EARs of firms with similar size, book-to-market ratio and momentum that announce earnings during the same calendar quarter. Panel C presents the raw EARs for capital distributing firms (NF < 0). Panel D presents the benchmark-adjusted EARs for capital distributing firms (NF < 0).

Panel A: Raw EARs (%), NF > 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	2.36	1.97	1.81	1.06	1.30	(2.20)
Equity	2	2.09	2.36	1.42	0.43	1.66	(2.88)
Ratio	3	1.04	1.10	0.89	-1.76	2.79	(4.83)
	High	0.55	0.37	-0.28	-1.48	2.02	(3.46)
	L-H	1.81	1.60	2.09	2.54		
		(4.15)	(3.71)	(3.54)	(3.47)		

Panel B: Benchmark-adjusted EARs (%), NF > 0

		Net External Financing					
		Low	2	3	High	L-H	
	Low	0.54	0.27	-0.03	-0.44	0.99	(1.83)
Equity	2	0.47	0.51	-0.22	-0.62	1.10	(2.05)
Ratio	3	-0.04	-0.02	-0.28	-2.30	2.26	(4.14)
	High	-0.49	-0.62	-1.17	-1.93	1.44	(2.54)
		1.03	0.88	1.14	1.48		
		(2.53)	(2.22)	(2.06)	(2.12)		

Panel C: Raw EARs (%), NF < 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	2.07	2.17	2.12	1.05	1.03	(1.68)
Equity	2	3.88	2.67	2.87	1.79	2.10	(3.30)
Ratio	3	3.05	2.62	2.74	2.62	0.43	(0.68)
	High	2.40	1.89	2.56	2.13	0.27	(0.52)
	L-H	-0.32	0.29	-0.44	-1.08		
		(-0.54)	(0.61)	(-0.93)	(-2.30)		

Panel D: Benchmark-adjusted EARs (%), NF < 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	0.91	0.41	0.56	-0.17	1.08	(1.82)
Equity	2	1.90	0.56	0.59	0.12	1.78	(2.94)
Ratio	3	1.22	0.66	0.56	0.55	0.67	(1.05)
	High	0.85	0.09	0.68	0.29	0.57	(1.11)
	L-H	0.06	0.32	-0.13	-0.46		
		(0.10)	(0.69)	(-0.27)	(-0.99)		

issuing more debt relative to equity. This is more consistent with the mispricing hypothesis than with the investment based explanations.

The annualized raw EARs on the four ER hedge portfolios range from 1.60% to 2.54%. To assess the economic significance of the results in Panel A, we compare these hedge portfolio returns with the results from other anomaly studies. La Porta, Lakonoishok, Shleifer and Vishny (1997) find that firms in the bottom book-to-market ratio quintile earn 3.22% more than those in the top book-to-market ratio quintile over the subsequent four earnings announcements[10]. The results reported by Titman, Wei and Xie (2004) suggest a zero-cost portfolio formed by longing firms in the lowest capital investment quintile and shorting those in the highest capital investment quintile generates 1.19% in market adjusted return. Thus, the debt-equity composition effect appears to have comparable economic significance to previously documented anomalies. In the analysis that follows, we will also examine the economic significance of the debt-equity composition effect on risk-adjusted basis. After adjusting for risk factors, we find the relative economic significance of the debt-equity composition effect to be even higher.

In Panel B, we present the benchmark-adjusted results for firms raising capital (NF > 0). The benchmark-adjusted EARs are defined as raw EARs minus the average EARs of firms with similar size, book-to-market ratio and momentum that announce earnings in the same calendar quarter. To the extent that the proceeds from financing activities are used to finance investment or asset growth, our bivariate sort also includes a partial control for the asset growth (Cooper, Gulen, and Schill (2008)) or investment (Titman, Wei and Xie (2004)) effects. There has been debate about whether the book-to-market, momentum and investment (asset growth) effects reflect market mispricing or compensation for risks. If we view these effects as market anomalies, it is unnecessary to control for these factors for testing the debt-equity substitution hypothesis. If firms

[10] La Porta, Lakonoishok, Shleifer and Vishny (1997) report that the equal weighted portfolio returns for the bottom two book-to-market deciles are -0.472% and 0.772% and for the top two book-to-market ratio deciles 3.2% and 3.532%. We calculate the returns on the hedge portfolio formed by shorting and longing the quintile portfolios as [(3.2% +3.532%)/2-(-0.472% + 0.772%)/2].

with low book-to-market ratio and high asset growth are systematically overpriced, it is natural for equity market timers to issue more equities relative to debt at times when their firms have lower book-to-market ratio and higher asset growth. However, if we view the stock return effects associated with size, book-to-market ratio, momentum and investment (asset growth) as compensation for risks, we need to control for these risk factors to make sure that the debt-equity composition effect we identify is not driven by known risk factors.

The results in Panel B are consistent with those in Panel A. Holding the NF quartiles constant, the benchmark-adjusted EARs generally increase as we move from low to high ER quartiles. The four ER low-minus-high hedge portfolios generate benchmark-adjusted EARs ranging from 0.88% to 1.48%, all statistically significant at 95% confidence level. Therefore, after controlling for other known anomalies and/or risk factors related to size, book-to-market ratio, momentum and investment (asset growth) and ROA, firms issuing more equity relative to debt still earn higher returns at subsequent earnings announcements than those issuing more debt relative to equity. These benchmark-adjusted hedge portfolio EARs cannot be directly compared with the results in La Porta, Lakonoishok, Shleifer and Vishny (1997) or those in Titman, Wei and Xie (2004) because earlier studies adjust EARs only for market returns or size returns. We will discuss the economic significance of these benchmark-adjusted EARs in our regression analysis.

Panels C and D present the earnings announcement test results for firms distributing capital (NF < 0). There appear to be no clear relation between NF, ER and EARs. Most of the hedge portfolios formed by longing and shorting the extreme NF (ER) portfolios are statistically insignificant. Following the logic in BCGW (2010), one possible explanation is that the cross-sectional variation in net financing is relatively small among firms distributing cash. Therefore, the information in this subsample is noisier than the information in the capital raising subsample. It should be emphasized that the results in Panels C and D only show that there is not enough "within" variation in EARs among the capital distributing firms. They do not necessarily mean that NF or ER has no effect on the earnings announcement returns of these firms. For example, even though the results in Panel D shows no clear relation between NF and benchmark-adjusted EARs, a comparison across Panel B and Panel D shows that capital distributing firms (NF<0) are much more likely to have positive benchmark-adjusted EARs than capital raising firms (NF>0).

Overall, our earnings announcement test results suggest that firms issuing more equity relative to debt earn higher raw and benchmark-adjusted EARs than those issuing more debt relative to equity. From the mispricing perspective, this can occur because firms tend to issue more equities when they are more overvalued. Investors are more negatively surprised when negative information about the overvalued firms is revealed at subsequent earnings announcements. Yet, the investment based theories provides no clear reason why equity issuers should earn lower earnings announcement returns than debt issuers.

3.2. Results from cross-sectional regressions

In this section, we examine the relation between net external financing, equity ratio and subsequent earnings announcement returns using regression analysis. The regression analysis allows us to control for additional factors that are known to affect stock returns. Besides, it provides an easy way to compare the economic magnitude across anomalies. We run cross-sectional regressions of earnings announcement returns on equity ratio, level of net external financing and various control variables. The regression model, is specified in equation (3).

$$EAR_{i,t+1} = \alpha + \beta_1 NEGNF_{i,t} \times ER_{i,t}^{dec} + \beta_2 POSNF_{i,t} \times ER_{i,t}^{dec} + \beta_3 NEGNF_{i,t} \times NF_{i,t} + \beta_4 POSNF_{i,t} \times NF_{i,t} + \beta_5 POSNF_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t} \quad (3)$$

In equation (3), the dependent variable is the 3-day buy-and-hold returns over the earnings announcement windows. $NEGNF_{i,t}$ is an indicator variable that takes the value of 1 when a firm has negative external financing for year t and 0 otherwise. $POSNF_{i,t}$ is an indicator variable for firms with positive external financing. ER^{dec} is the transformed decile ranking of equity ratio.

Following Mashruwalaa, Rajgopala, and Shevli, we rank firms into deciles by equity ratio and then transform the decile ranks into a value between -0.5 and 0.5. When the variable is so transformed, its coefficient can be interpreted as the EARs earned on a hedge portfolio formed by shorting firms in the lowest equity ratio decile and longing those in the highest equity ratio decile. Following BCGW (2010), we use the interaction terms to allow the signs and magnitudes of coefficients of the ER and NF variables to differ between firms raising capital and those distributing capital. Both the descriptive statistics for the two variables and the results from portfolio sorts suggest that it is important to allow the coefficients to vary between the two subsamples. We estimate the model using the Fama MecBeth (1973) procedure, which involves running cross-sectional regressions each calendar quarter and then averaging the coefficients across quarters. We adjust for the autocorrelation in the quarterly coefficients using the adjustment factor proposed by Abarbanell and Bernard (2000)[11].

Table 1.3 summarizes the regression results for the model in equation (3). Model (1) is similar to the portfolio sort analysis in Panel A of Table 1.2 in that it includes only the interaction terms related to NF and ER^{dec}. Consistent the results from portfolio sorts, the coefficients for POSNF × NF and POSNF × ER^{dec} are significantly negative. The coefficient for POSNF × ER^{dec} is -0.6458, which indicates that the hedge portfolio strategy of longing capital raising firms in the lowest ER decile and shorting those in the highest ER decile generates about 2.58% in EARs (0.6458 × 4) over the four subsequent earnings announcements. This is of slightly larger economic magnitude than those reported in Panel A of Table 1.2 because the hedge portfolios in Table 1.3 are formed by longing and shorting more extreme ER portfolios (longing and shorting extreme deciles vs longing and shorting extreme quartiles).

[11] We adjust for the autocorrelation in the quarterly coefficient by multiplying the unadjusted standard error to an adjustment factor $\sqrt{\frac{1+\emptyset}{1-\emptyset} - \frac{2\emptyset(1-\emptyset^{n})}{n(1-\emptyset)^{2}}}$, where n is the number of quarterly coefficients and Ø the first order autoregressive coefficient estimated from the respective quarterly coefficients.

Model (2) includes log(MV), log(BM) and MOM as control variables for the size, book-to-market and momentum effects. The coefficients for these control variables have expected signs and are statically significant. The regression results suggest that earnings announcement returns tend to be higher for smaller firms, high book-to-market firms and firms with higher stock return momentums. More importantly, the coefficients for POSNF × NF and POSNF × ER^{dec} are both negative and statistically significant at conventional significance levels. Therefore, after controlling for the size, book-to-market and momentum effects, the regression results are still consistent with the mispricing hypothesis.

Model (3) includes asset growth and ROA as two additional control variables. Motivated by the q-theory of investment, Chen and Zhang (2010) propose an alternative three factor model. They find that the investment and ROA factors can explain a significant portion of the cross-sectional variation in stock returns and several well known anomalies. Since the investment based explanations for financing anomalies are related to the q-theory of investment, it makes sense to check whether the debt-equity composition effect is robust to the inclusion of investment (asset growth) and ROA as control variables. Consistent with the predictions by Chen and Zhang (2010), the coefficient for asset growth, which we use as a comprehensive measure for firms' investment activities, is negative and significant. The coefficient for ROA has the correct sign but is statistically insignificant. Chen and Zhang (2010) suggest that the ROA effect is related to the momentum effect. This could explain why the coefficient for ROA is insignificant when the model includes MOM as a control variable. After controlling for asset growth, the coefficient for POSNF × NF decreases in magnitude from -1.0759 in Model (2) to – 0.2569, which is statistically indistinguishable from 0. This suggests there might be a relation between the net external financing effect and the firms' investment activities. However, the coefficient for POSNF × ER^{dec} changes little from Model (2). It remains significant with a t value of -5.47. The results for Model (3) show that the debt-equity composition effect still exists after controlling for firms' investment activities. Therefore, the investment based theories cannot explain why equity

Table 1.3. Regression of earning announcement returns on external financing variables

This table reports the regression of earnings announcement returns (EARs) on net external financing (NF) and equity ratio (ER). We calculate the independent variables at the end of June of each year t and match them with the earnings announcements that occur between July of year t and June of year t + 1. EARs are calculated as the 3-day buy-and-hold returns surrounding the earnings announcements. NF is net external financing, defined as the net amount of cash from issuing and repurchasing debt and equity securities scaled by average assets. ER^{dec} is the decile ranking for equity ratio, defined as the proportion of net equity to net cash raised. The decile ranking is transformed to a value between -0.5 to 0.5. POSNF is an indicator variable that takes the value of one for firms with positive net external financing. NEGNF is an indicator variable that takes the value of one firms with negative net external financing. Log(MV) is the logarithm of the market value of equity at the end of June of year t. Log(B/M) is the logarithm of the book-to-market ratio, defined as the book value of equity as of the fiscal year end that occur in calendar year t – 1 scaled by the market value of equity at the end of December of year t - 1. Growth is the change in assets scaled by lagged assets. ROA is operating income before depreciation scaled by lagged book assets. The models are estimated using the Fama MecBeth procedure. The standard errors are calculated with the time series of quarterly coefficients, with the autocorrelation in the quarterly coefficients adjusted using the method in Abarranel and Bernard (2000). The t statistics are reported in the parentheses. The adjusted R^2 statistics are the mean adjusted R^2 for the 152 quarterly regressions.

	Intercept	POSNF × NF	NEGNF × NF	POSNF × ER^{dec}	NEGNF × ER^{dec}	POSNF	Log(MV)	Log(BM)	MOM	Growth	ROA	R&D	Adjusted R^2 (%)
(1)	0.0058	-0.0104	-0.0117	-0.0065	0.0006	-0.0017							0.24
	(6.80)	(-5.86)	(-2.58)	(-9.01)	(0.75)	(-4.18)							
(2)	0.0161	-0.0108	-0.0079	-0.0046	0.0010	-0.0009	-0.0009	0.0021	0.0011				0.62
	(9.13)	(-5.64)	(-1.68)	(-6.48)	(1.44)	(-1.94)	(-6.84)	(6.58)	(1.93)				
(3)	0.0175	-0.0026	-0.0027	-0.0039	0.0009	-0.0011	-0.0009	0.0017	0.0011	-0.0036	0.0017		0.70
	(9.89)	(-1.14)	(-0.54)	(-5.42)	(1.30)	(-2.47)	(-7.81)	(5.21)	(1.90)	(-5.16)	(0.97)		
(4)	0.0175	-0.0024	-0.0029	-0.0040	0.0009	-0.0011	-0.0009	0.0017	0.0011	-0.0036	0.0019	0.0023	0.75
	(10.00)	(-1.09)	(-0.58)	(-5.54)	(1.27)	(-2.51)	(-7.89)	(5.29)	(1.93)	(-5.05)	(1.06)	(0.47)	

issuers earn lower earnings announcement returns than debt issuers. In Model (4), we add R&D as an additional control variable to Model (3). There appears to be no evidence that R&D is related to subsequent earnings announcement returns. We will go back to the R&D issue in that analysis that follows.

To assess the economic significance of the debt-equity composition effect, we re-estimate Model (3) after transforming the Log(BM) variable to its decile ranking BM^{dec}. The coefficient for BM^{dec} is 0.3749, which indicates that the hedge strategy based on longing and shorting extreme book-to-market deciles generates about 1.50% (0.3749 × 4) in abnormal return over the subsequent four earnings announcements. In comparison, the coefficient for POSNF × ER^{dec} is -0.4035, which is equivalent to 1.64% in abnormal return over the four earnings announcements. We also re-estimate Model (3) after transforming Log(MV), Log(BM), MOM, Growth and ROA all into their decile rankings. We find the economic magnitude of the debt-equity composition effect is similar to the magnitude of the book-to-market effect and large than those of the MOM and ROA effects.

Overall, the earnings announcement test results suggest that firms issuing more equity relative to debt earn lower returns at subsequent earnings announcements than those issuing more debt than equity. This debt-equity composition effect is statistically and economically significant. It still exists after controlling for the size, book-to-market, momentum, investment (asset growth) and ROA effects. This suggests that investors are more negatively surprised by equity issuers than by debt issuers. From the mispricing perspective, such debt-equity composition effect can occur when managers at more overvalued firms issue more equity relative to debt to exploit the market mispricing. Our findings are thus consistent with the view that market mispricing plays an important role in driving the financing anomalies.

4. Debt-equity choice, growth options and future stock returns

The results in Section 3 suggest that heavy equity issuers earn lower earnings announcement returns than heavy debt issuers. Our findings are thus consistent with the market timing hypothesis, but inconsistent with the evidence provided by BCGW (2010). We hypothesize that BCGW (2010) find no evidence of market timing because of the confounding effect associated with the equity financing of growth options. In this section, we provide evidence in support of this hypothesis. We use firms' R&D expenditure, defined as R&D spending scaled by lagged assets, as the proxy for firms' propensity to invest in growth options. R&D expenditure is one of the most intuitive proxies for the investment in growth options because firms with high R&D expenditures are more likely to invest in growth options. However, it is unlikely that R&D expenditure can fully capture firms' investments in growth options because not all growth options are R&D related. In this sense, the evidence presented in this section only provides a very conservative estimate of debt-equity composition effect in year-ahead stock returns. Our goal is not to provide a precise point estimate of the market timing effect associated with firms' debt-equity choices, but to verify whether different conclusions about the mispricing hypothesis can be reached before and after controlling for the new investment-in-growth-options effect.

4.1 Results from portfolio sorts

We follow the same portfolio sort procedure as in Section 3. At the end of June of each year t, we sort firms into quartiles by the level of net external financing (NF). Then we divide each NF quartile into four portfolios by equity ratio (ER). The sorts are done separately for capital raising firms (NF > 0) and capital distributing firms (NF < 0). We examine how the raw and benchmark-adjusted year-ahead stock returns vary across the NF × ER portfolios. The raw year-ahead stock returns are measured as the 12 month buy-and-hold returns (BHARs) from July of year t to June of year t + 1. The benchmark-adjusted BHARs are defined as raw BHARs minus the average BHARs of firms with similar size, book-to-market ratio and stock return momentum.

Table 1.4. 12 month buy-and-hold returns by ER and NF quartiles

This table reports the 12-month buy-and-hold returns (BHARs) by net external financing (NF) and equity ratio (ER) quartiles. At the end of June of each year t, we sort firms into quartiles by NF. Then we divide each NF portfolio into quartiles by ER. For each year, we calculate the equally weighted buy-and-hold return (BHAR) for each NF-ER portfolio. The returns presented in the table are averages over all formation periods. For each year, we also form hedge portfolios by longing stocks in the lowest NF (ER) quartiles and shorting stocks in the highest NF (ER) quartiles. The time series standard errors of the hedge portfolio returns are used to calculate the t-statistics in the parentheses. Panel A presents the raw BHARs for capital raising firms (NF >0). The raw BHARs are defined as the 12 month buy-and-hold returns from July of year t to June of year t + 1. Panel B presents the benchmark-adjusted BHARs for capital raising firms (NF > 0). The benchmark-adjusted BHARs are defined as raw BHARs minus the average BHARs of firms with similar size, book-to-market ratio and momentum. Panel C presents the raw BHARs for capital distributing firms (NF < 0). Panel D presents the benchmark-adjusted BHARs for capital distributing firms (NF < 0).

Panel A: Raw BHARs, NF > 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	19.27	16.70	15.45	7.70	11.57	(6.08)
Equity	2	15.21	15.36	11.81	2.32	12.89	(5.17)
Ratio	3	16.50	13.64	9.28	3.35	13.14	(5.33)
	High	12.71	11.38	7.86	2.50	10.22	(4.05)
	L-H	6.56	5.31	7.59	5.21		
		(3.09)	(1.68)	(2.61)	(1.58)		

Panel B: Benchmark-adjusted BHARs, NF > 0

		Net External Financing					
		Low	2	3	High	L-H	
	Low	2.62	0.91	0.14	-5.72	8.34	(5.21)
Equity	2	-0.61	-0.61	-2.58	-9.86	9.25	(5.14)
Ratio	3	3.83	-0.04	-3.09	-6.88	10.71	(5.22)
	High	0.12	-0.42	-3.42	-7.32	7.44	(3.62)
		2.50	1.32	3.55	1.60		
		(1.74)	(0.64)	(1.68)	(0.65)		

Panel C: Raw BHARs, NF < 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	16.86	19.30	17.82	17.37	-0.51	(-0.22)
Equity	2	19.88	20.09	17.86	17.53	2.34	(0.83)
Ratio	3	21.22	20.47	18.91	19.69	1.53	(0.70)
	High	21.56	21.23	17.79	17.86	3.70	(1.92)
	L-H	-4.70	-1.93	0.02	-0.49		
		(-1.75)	(-0.97)	(0.01)	(-0.23)		

Panel D: Benchmark-adjusted BHARs, NF < 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	2.82	4.42	2.49	3.69	-0.87	(-0.39)
Equity	2	3.33	3.04	0.58	1.75	1.58	(0.65)
Ratio	3	4.98	2.98	1.80	2.43	2.55	(1.22)
	High	6.14	5.26	1.39	1.42	4.71	(2.85)
	L-H	-3.32	-0.84	1.10	2.26		
		(-1.41)	(-0.46)	(0.71)	(1.16)		

Each year, we calculate the equal weighted raw and adjusted BHARs for each of the NF × ER portfolios. By so doing, we obtain 38 years of equal weighted portfolio BHARs for each of the NF×ER portfolios from July 1972 to June 2010. Tables 1.4 and 1.5 report the time series means of these portfolio returns. The significance levels of the low-minus-high hedge portfolios are based on time series standard errors. If the mispricing hypothesis holds, firms issuing (repurchasing) more equity relative to debt will earn lower (higher) year-ahead stock returns than those issuing (repurchasing) more debt relative to equity.

In Table 1.4, we present the results without controlling for the investment in new growth options. We keep the discussion about Table 1.4 concise because our goal is only to show that, without controlling for R&D, our results are consistent with the findings by BCGW (2010). BCGW (2010) reports only benchmark-adjusted results. For completeness, we report both the raw and benchmark-adjusted BHARs for the NF × ER portfolios. Panel A of Table 1.4 presents the raw BHARs for the capital raising firms (NF > 0). Holding the NF quartiles constant, the raw BHARs appear to decrease as we move from the low to high ER portfolios. However, only two of the ER hedge portfolios generate returns that statistically different from 0 at the 5% significance level. The other two have significance level below 10%. Panel B presents the benchmark-adjusted BHARs for capital raising firms (NF > 0). Since the returns in Panel B are benchmark-adjusted, they are more comparable to the portfolio sort results reported by BCGW (2010). So are the results. We find the portfolio BHARs decrease monotonically with the level of net external financing. However, holding the NF quartiles constant, there is no clear relation between the equity ratio and future stock returns. In Panels C and D, we present the results for the capital distributing firms. There appear to be no consistent relation between future stock return and either the level or the composition of net external financing. Overall, the results in Table 1.4 are consistent with those reported by BCGW (2010). Without controlling for the investment in growth options, we find no evidence of equity market timing.

Table 1.5. 12 month buy-and-hold returns by ER and NF quartiles, after excluding high R&D firms

This table reports the 12-month buy-and-hold returns (BHARs) by net external financing (NF) and equity ratio (ER) quartiles. At the end of June of each year t, we sort firms into quartiles by NF. Then we divide each NF portfolio into quartiles by ER. For each year, we calculate the equally weighted buy-and-hold return (BHAR) for each NF-ER portfolio. The returns presented in the table are averages over all formation periods. For each year, we also form hedge portfolios by longing stocks in the lowest NF (ER) quartiles and shorting stocks in the highest NF (ER) quartiles. The time series standard errors of the hedge portfolio returns are used to calculate the t-statistics in the parentheses. Panel A presents the raw BHARs for capital raising firms (NF >0). The raw BHARs are defined as the 12 month buy-and-hold returns from July of year t to June of year t + 1. Panel B presents the benchmark-adjusted BHARs for capital raising firms (NF > 0). The benchmark-adjusted BHARs are defined as raw BHARs minus the average BHARs of firms with similar size, book-to-market ratio and momentum. Panel C presents the raw BHARs for capital distributing firms (NF < 0). Panel D presents the benchmark-adjusted BHARs for capital distributing firms (NF < 0) .

Panel A: Raw BHAR, NF > 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	19.14	16.08	14.23	8.57	10.56	(5.27)
Equity	2	13.75	14.96	11.44	2.40	11.35	(4.47)
Ratio	3	15.22	11.72	8.25	0.13	15.09	(4.95)
	High	10.65	8.15	5.55	-1.59	12.24	(4.14)
	L-H	8.48	7.93	8.68	10.16		
		(5.18)	(2.59)	(3.73)	(3.29)		

Panel B: Benchmark-adjusted BHAR, NF > 0

		Net External Financing					
		Low	2	3	High	L-H	
	Low	2.26	0.23	-1.29	-5.26	7.52	(4.41)
Equity	2	-2.01	-0.96	-3.09	-10.64	8.63	(4.15)
Ratio	3	1.92	-2.26	-4.42	-10.80	12.72	(4.78)
	High	-2.75	-3.97	-6.14	-11.67	8.93	(3.27)
		5.01	4.20	4.84	6.41		
		(3.35)	(1.77)	(2.75)	(2.29)		

Panel C: Raw BHAR, NF < 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	15.95	17.36	16.05	16.25	-0.30	(-0.13)
Equity	2	19.58	19.74	17.00	15.26	4.32	(1.70)
Ratio	3	20.49	20.17	18.98	18.96	1.53	(0.64)
	High	20.11	20.39	16.70	17.33	2.79	(1.41)
	L-H	-4.16	-3.02	-0.64	-1.08		
		(-1.33)	(-1.39)	(-0.39)	(-0.48)		

Panel D: Benchmark-adjusted BHAR, NF < 0

		Net External Financing					
		How	2	3	High	L-H	
	Low	1.58	2.14	0.50	2.19	-0.61	(-0.28)
Equity	2	2.81	2.54	-0.28	-0.63	3.44	(1.70)
Ratio	3	4.13	2.33	1.77	1.31	2.81	(1.22)
	High	4.32	4.29	-0.02	0.57	3.74	(2.11)
	L-H	-2.74	-2.15	0.53	1.62		
		(-1.03)	(-1.09)	(0.36)	(0.77)		

Our approach to mitigating the investment-in-growth-options effect is straightforward: we compare the NF × ER portfolio BHARs after excluding firms with R&D expenditure higher than 5% of lagged assets. Since high R&D firms are more likely to invest in growth options, the confounding investment-in-growth-options effect is likely to be the strongest among these firms. If our hypotheses regarding the market timing effect and the investment-in-growth-options effect hold, we should detect stronger evidence for market timing after excluding firms that are most seriously affected by the confounding effect.[12] Table 1.5 presents the portfolio sort results after excluding the high R&D firms. In Panel A, we present the raw BHARs for firms raising capital (NF > 0). Holding the NF quartiles constant, the raw BHARs decrease with equity ratio with reasonable monotonicity. The BHAR spreads between low and high ER portfolios are larger than those reported in Panel A of Table 1.4. The returns on all ER portfolios are positive and statistically significant at conventional significance levels.

As we argue in Section 3, if we view the size, book-to-market and momentum effects as anomalies, we do not have to control for these factors in testing the market timing hypotheses. If so, the raw BHAR results in Panel A can be interpreted as solid evidence for the market timing hypothesis. However, if we view the stock return effects associated with size, book-to-market ratio, momentum as compensation for risks, we need to check whether the debt-equity composition effect still holds after controlling for these risk factors. In Panel B of Table 1.5, we present the benchmark-adjusted BHARs for firms raising capital (NF > 0). We first examine how the benchmark-adjusted BHARs change across the portfolios. Except for in the lowest NF quartile, the benchmark-adjusted BHARs decrease monotonically as we move from the lowest to the highest ER portfolio.[13] The results are less monotonic for firms in the lowest NF quartile,

[12] In Table 1.5., we do not re-sort the portfolios after excluding the high R&D firms. We examine the results after re-sorting as robustness check. We find re-sorting strengthens our results.
[13] Bradshaw, Richardson and Sloan (2006) sort firms into deciles by net external financing. Their results are not perfectly monotonic, either. For example, they find the size-adjusted BHARs for the lowest NF portfolio, the third lowest NF portfolio and the fifth lowest portfolio are, respectively, 0.041, 0.020 and 0.043. Considering that we perform the more challenging task of bivariate sort, the degree of monotonicity displayed in Panel B is already very impressive.

perhaps because they raise smaller amount of cash through external financing.[14] The mean NF for these firms is 0.018, as opposed to 0.39 for those in the highest NF quartile. When firms raise only a small amount of cash, managers are less concerned about whether they are overvalued. Consequently, the equity ratio is a noisier proxy for managers' market timing incentives for these firms. Then we examine the returns on the ER hedge portfolios. The four low-minus-high portfolios generate benchmark-adjusted BHARs ranging from 4.2% - 6.41% per annum. For the ER hedge portfolio in the second lowest NF quartile, the hedge returns are statistically different from 0 at 10% significance level. The hedge returns on the other three portfolios are significant at 1% significance level. Therefore, after excluding firms that are most seriously affected by the investment-in-growth-options effect, we find heavy equity issuers have lower year-ahead stock returns than heavy debt issuers.

We present the results for capital distributing firms (NF < 0) in Panel C and Panel D. For capital distributing firms, there appear to be no consistent relation between ER, NF and futures stock return. Following the argument by BCGW (2010), the results in Panel C and D are "not surprising because the cross-sectional variation in net financing among firms distributing capital is relatively small". They only show that there is not enough "within" variation in BHARs among the capital distributing firms. They do not necessarily mean that NF or ER has no effect on the stock returns of these firms. For example, even though the returns on the NF hedge portfolios in Panel D are statistically insignificant, a comparison between Panel B and Panel D shows that, on average, capital distributing firms (NF < 0) have higher returns than capital raising firms (NF > 0).

Overall, the evidence in Table 1.5 supports our hypotheses regarding the market timing effect and the investment-in-growth-options effect. Without controlling for the investment in

[14] Interestingly, some of the firms in the lowest ER portfolio in the lowest NF quartile have low NF because the equity they issue offsets the debt they issue. These firms have larger net equity (debt) issue size than firms in the middle two ER portfolios. This can explain why the BHAR difference between the lowest and the highest ER portfolios is significant in the lowest NF quartile.

growth options, our results are consistent with the findings by BCGW (2010). However, after excluding firms that are most likely to be affected by the confounding effect related to the investment in growth options, we find firms issuing more equity relative to debt tend to have lower future stock returns even after controlling for the level of net external financing.

4.2 Results from cross-sectional regressions

In this section, we examine the relation between equity ratio and future stock returns using cross-sectional regressions. We regress raw BHAR on NF, ER^{dec} and various control variables. The regressions are estimated using the Fama MacBeth (1973) procedure. We adjust for the autocorrelation in the annual coefficients using the method proposed by Abarranel and Bernard (2000).

The regression results are presented in Table 1.6. The two benchmark models, Model (1) and Model (2), do not include R&D as a control variable. Model (1) includes control variables for the size, book-to-market and momentum effects. Consistent with the findings by BCGW (2010), the coefficients for POSNF × ER^{dec} and NEGNF × ER^{dec} are statistically insignificant in the presence of POSNF × NF and NEGNF × NF. Model (2) includes asset growth and ROA as additional control variables. The coefficients for POSNF × ER^{dec} and NEGNF × ER^{dec} remain statistically insignificant. Moreover, the magnitude of the coefficient for POSNF × NF decreases to statistically insignificant level, suggesting a possible relation between the level effect and firms' investment activities as captured by the asset growth variable. The results from Model (1) and Model (2) are consistent with the findings by BCGW (2010). Without controlling for the investment in new growth options, there is no evidence that the debt-equity composition of net external financing is related to future stock returns.

In Model (3) and Model (4), we add R&D as a control variable to Model (1) and Model (2). Model (5) includes a high R&D dummy, which takes the value of one for firms with R&D expenditure higher than 5% of lagged assets and 0 otherwise, to control for the investment-in-

Table 1.6. Regression of year-head stock returns on equity ratio and net external financing

This table reports the regression of year-ahead stock returns on net external financing and equity ratio. The dependent variable is the 12-month buy-and-hold return (BHARs). We calculate the independent variables at the end of June of each year t and match them with BHARs from July of year t to June of year t + 1. NF is net external financing, defined as the net amount of cash from issuing and repurchasing debt and equity securities scaled by lagged assets. ER is the decile ranking for equity ratio, defined as the proportion of net equity to net cash raised. The decile ranking is transformed to a value between -0.5 to 0.5. POSNF is an indicator variable that takes the value of one for firms with positive net external financing. NEGNF is an indicator variable that takes the value of one firms with negative net external financing. Log(MV) is the logarithm of the market value of equity at the end of June of year t. Log(B/M) is the logarithm of the book-to-market ratio, defined as the book value of equity as of the fiscal year end that occur in calendar year t – 1 scaled by the market value of equity at the end of December of year t - 1. Growth is the change in assets scaled by lagged assets. ROA is operating income before depreciation scaled by lagged book assets. The models are estimated using the Fama MecBeth procedure. The standard errors are calculated with the time series of quarterly coefficients, with the autocorrelation in the quarterly coefficients adjusted using the method in Abarranel and Bernard (2000). The t statistics are reported in the parentheses. The adjusted R^2 statistics are the mean adjusted R^2 of the annual regressions.

	Intercept	POSNF ×NF	NEGNF ×NF	POSNF $\times ER^{dec}$	NEGNF $\times ER^{dec}$	POSNF	Log(MV)	Log(BM)	MOM	Growth	ROA	R&D	High R&D	Adjusted R^2 (%)
(1)	0.2739	-0.1801	-0.0702	-0.0199	0.0202	-0.0233	-0.0072	0.0378	0.0300					5.15
	(2.26)	(-8.80)	(-0.69)	(-0.97)	(1.65)	(-3.67)	(-1.00)	(4.67)	(1.76)					
(2)	0.2766	-0.0156	-0.0098	-0.0112	0.0155	-0.0258	-0.0092	0.0392	0.0274	-0.0780	0.1650			5.67
	(2.37)	(-0.61)	(-0.10)	(-0.61)	(1.33)	(-4.30)	(-1.38)	(4.80)	(1.70)	(-8.59)	(3.88)			
(3)	0.2436	-0.2071	-0.1000	-0.0469	0.0214	-0.0220	-0.0055	0.0474	0.0296			0.4923		5.82
	(2.11)	(-8.38)	(-1.02)	(-3.55)	(1.77)	(-3.14)	(-0.81)	(7.87)	(1.76)			(3.23)		
(4)	0.2543	-0.0211	-0.0260	-0.0403	0.0151	-0.0259	-0.0089	0.0501	0.0264	-0.0861	0.2281	0.5989		6.33
	(2.26)	(-0.79)	(-0.28)	(-3.10)	(1.27)	(-3.99)	(-1.36)	(7.71)	(1.61)	(-9.51)	(6.45)	(3.93)		
(5)	0.2515	-0.0077	-0.0246	-0.0384	0.0124	-0.0266	-0.0084	0.0468	0.0259	-0.0805	0.1935		0.0855	6.31
	(2.24)	(-0.33)	(-0.25)	(-3.07)	(1.02)	(-4.43)	(-1.30)	(7.10)	(1.62)	(-9.21)	(5.32)		(3.09)	
(6)	0.2495	-0.0709	-0.0157	-0.0505	0.0237	-0.0289	-0.0085	0.0445	0.0339	-0.0662	0.2414			5.46
	(2.14)	(-2.69)	(-0.16)	(-2.97)	(2.09)	(-4.16)	(-1.22)	(5.15)	(2.01)	(-7.91)	(4.97)			
(7)	0.2755	-0.1234	0.0456	-0.0433	0.0227	-0.0401	-0.0093	0.0464	0.0352	-0.0552	0.2329			5.38
	(2.21)	(-2.61)	(0.60)	(-1.98)	(1.10)	(-3.91)	(-1.21)	(5.47)	(1.86)	(-2.65)	(4.22)			

growth-options effect. For all three models, the coefficients for POSNF × ER^{dec} turn statistically significant. For example, in Model (4), the coefficient for POSNF × ER is -0.0469, which is 3.6 standard errors away from 0. Therefore, a hedge portfolio formed by longing the capital raising firms in the lowest equity ratio decile and shorting those in the highest decile earn 4.69% per year. This is a conservative estimate of the market timing effect related to firms' debt-equity choices because R&D spending does not fully control for investment in growth options.

In Models (3), (4) and (5), we assume that set missing R&D value to zero, assuming that firms with missing R&D spend zero or negligible amount on research and development[15]. To make sure that our results are not driven by this assumption, we estimate two additional models that do not explicitly use R&D as a control variable. In Model (6), we estimate Model (2) after excluding firms that are known to have R&D expenditure higher than 5% of lagged assets. In Model (7), we estimate Model (2) after excluding firms that are known to have R&D expenditure higher than 5% of lagged assets and those with missing R&D. In Model (6), the coefficient for the POSNF × ER^{dec} variable is -0.0505, which is 2.97 standard errors away from zero. In Model (7), the coefficient for the POSNF × ER^{dec} variable is -0.0433, with a t statistic of -1.98. The results in these two models provide further evidence that firms issuing more equity relative to debt earn lower year-ahead stock returns after partially controlling for the investment-in-growth-options effect in the models.

The R&D related variables are significantly positive in all models where they are present. For example, the coefficient for the high R&D dummy in Model (5) is 0.0855, indicating that high R&D firms earn 8.55% more per annum than low R&D firms. However, in Model (4) of Table 1.3, the coefficients for R&D are not significant, providing no evidence that investors are

[15] By the SEC rule adopted in 1972, firms are required to report estimated amount of R&D when (a) it is material, (b) it exceeds 1% of sales, or (c) a policy or deferral or amortization of R&D expenses is pursued. If firms consider their R&D spending immaterial and indicate this, e.g., by reporting 0 R&D in 10K, Compustat will record 0. A Comustat record of "not available" could happen in three situations: (a) firms say nothing about R&D in 10K, (b) firms' R&D information is randomly missing, or (c) firms report R&D, but Compustat concludes that their definitions of R&D do not conform (Griliches, 1984). Julio, Kim and Weisbach (2008) suggests that it is "typical in the previous literature" to set missing R&D to 0.

systematically surprised by high R&D firms at the information rich earnings announcement events. Thus, the higher year-ahead returns on R&D are more likely to be the rationally expected components of stock returns than the unexpected components related to the surprises to investors. This is consistent with the view that investors require higher return for holding the equities of high R&D firms (Berk, Green and Naik (2004) and Li (forthcoming)). More importantly, this explains why the earnings announcement test can detect evidence of market timing without including R&D as a control variable. Since the R&D related stock returns effects, which we use as a proxy for the investment-in-growth-options effect, are rationally expected, they are spread more smoothly over the year. However, the market timing effect is more concentrated during the earnings announcement periods. Therefore, relative to the investment-in-growth-options effect, the market timing effect is stronger during the earnings announcement days. In other words, the market timing effect related to the debt-equity composition of external financing is more easily detected at earnings announcements, but offset by the new growth options effect during other time of the year.

5. Equity ratio and analysts' forecasts of firms' long term growth rates

Previous research shows that expectational errors in long term growth rates are closely related to stock market predictability (e.g., Dechow and Sloan (1997) and La Porta (1996)). For example, Dechow and Sloan (1997) find that naïve reliance on analysts' forecasts of future earnings growth can explain over half of the higher returns to contrarian investment strategies. In search for further evidence for the market timing hypothesis, we examine the relation between equity ratio and market expectation of long term growth rates in this section. If the market timing hypothesis holds, firms will issue more equity relative to debt when the market expectations, as proxied by analysts' forecasts, are overly optimistic. Consequently, heavy equity issuers will have more negative forecast errors than heavy debt issuers.

Following previous studies, we use the mean analysts' forecast (LTG) in the I/B/S/E database as the proxy for market expectations about firms' long term growth rates. The LTG variable is not available for all firms. We thus need to decide whether to use the NF × ER breakpoints for the entire sample or to re-sort the NF × ER portfolios for these firms alone. We choose to use the NF × ER breakpoints for the entire sample so that the results are more comparable across sections. We also re-sort the firms into NF × ER breakpoints for robustness check and find stronger support for our hypothesis.

Table 1.7 presents the analysts' forecasts errors in firms' long term growth rates (LTGFE) by external financing (NF) and equity ratio (ER). Panel A presents the raw LTGFEs for capital raising firms (NF > 0). The mean LTGFEs for all NF × ER portfolios are negative, suggesting that analysts are in general overly optimistic about firms' growth prospects. More importantly, holding the NF quartiles constant, the mean LTGFEs generally decrease as we move from the lowest ER portfolios to the highest ER portfolios. The LTGFE spreads between the low and high ER portfolios range from 4.84% to 10.76%, all with statistically significant t values. These results suggest that firms choose to issue more equity relative to debt when their growth prospects are more overestimated by the market.

Strictly speaking, it is unnecessary to make benchmark-adjustments to LTGFEs for testing the market timing hypothesis. Equity market timers will issue more equities relative to debt when the market severely overestimates their growth prospects, regardless of whether the analysts' overoptimism is driven by size, book-to-market ratio or momentum. We nevertheless examine the benchmark-adjusted LTGFEs to assess whether analysts are more optimistic about equity issuers than they are about debt issuers with similar size, book-to-market ratio and momentum. Panel B presents the benchmark-adjusted LTGFEs for firms raising capital (NF > 0). Holding the NF quartiles constant, the benchmark-adjusted LTGFEs turn more negative as equity ratio increases. The low-minus-high LTGFE spreads range from 2.21% to 8.27%. One of the spreads is statistically significant at 10% significance level and all three others at 1% significance

Table 1.7. Analysts' forecast errors in long term growth rate by net external financing and equity ratio

This table reports the errors in analysts' forecasts of long term growth rate by net external financing (NF) and equity ratio (ER) quartiles. At the end of June of each year t, we sort firms into quartiles by NF. Then we divide each NF portfolio into quartiles by ER. We calculate analysts' forecast errors as realized future growth rates minus analysts' forecasts of long term growth rates. The future growth rates in EPS are obtained by fitting an ordinary least squares line through the logarithm of the EPS (excluding extraordinary items) reported for the fiscal year ending in calendar year t – 1 and the EPS for the next five years. The analysts' forecasts of long term growth rates are the mean analysts' forecasts of five year growth rate in the I/B/E/S database that are available in June of year t. The forecast errors presented in the table are averages over all formation periods. For each year, we also calculate the forecast error spreads between the lowest NF (ER) portfolios and the highest NF (ER) portfolios. The time series standard errors of these spreads are used to calculate the t-statistics in the parentheses. Panel A presents the raw growth rate forecasts errors for capital raising firms (NF >0). Panel B presents the benchmark-adjusted growth rate forecast errors for capital raising firms (NF > 0). The benchmark-adjusted growth rate forecast errors are defined as raw growth rate forecast errors minus the average growth rate forecast errors of firms with similar size, book-to-market ratio and momentum. Panel C presents the raw growth rate forecast errors for capital distributing firms (NF < 0). Panel D presents the benchmark-adjusted growth rate forecast errors for capital distributing firms (NF < 0).

Panel A: Raw LTG forecast errors, NF > 0

		Net External Financing					
		Low	2	3	High	L-H	
	Low	-12.92	-13.86	-14.11	-16.99	4.07	(2.68)
Equity	2	-14.94	-11.94	-15.15	-18.39	3.46	(1.72)
Ratio	3	-19.40	-14.19	-17.64	-22.08	2.68	(1.09)
	High	-20.55	-18.70	-21.97	-27.75	7.20	(4.61)
	L-H	7.63	4.84	7.86	10.76		
		(6.87)	(2.73)	(5.23)	(4.63)		

Panel B: Benchmark-adjusted LTG forecast errors, NF > 0

		Net External Financing					
		Low	2	3	High	L-H	
	Low	0.72	0.71	1.08	0.80	-0.08	(-0.06)
Equity	2	-0.27	2.54	0.20	-0.27	0.00	(0.00)
Ratio	3	-1.13	1.17	-2.43	-1.97	0.84	(0.47)
	High	-2.52	-1.50	-3.59	-7.47	4.95	(3.85)
		3.24	2.21	4.67	8.27		
		(3.82)	(1.86)	(4.04)	(4.89)		

Panel C: Raw LTG forecast errors, NF < 0

		Net External Financing					
		Low	2	3	High	L-H	
	Low	-17.03	-14.37	-14.95	-16.55	-0.48	(-0.31)
Equity	2	-14.03	-8.16	-12.24	-12.28	-1.75	(-1.03)
Ratio	3	-18.21	-12.91	-13.99	-14.42	-3.79	(-1.55)
	High	-18.34	-16.47	-16.38	-14.83	-3.51	(-4.05)
	L-H	1.31	2.09	1.43	-1.72		
		(0.93)	(1.52)	(1.02)	(-1.51)		

Panel D: Benchmark-adjusted LTG forecast errors, NF < 0

		Net External Financing					
		Low	2	3	High	L-H	
	Low	0.84	1.35	0.60	-0.66	1.50	(1.08)
Equity	2	1.80	5.38	2.82	2.45	-0.65	(-0.43)
Ratio	3	-2.32	1.27	-0.15	0.23	-2.55	(-0.97)
	High	0.00	-0.06	0.03	0.48	-0.48	(-0.63)
	L-H	0.84	1.40	0.57	-1.14		
		(0.61)	(1.00)	(0.44)	(-1.15)		

level. The evidence in Panel B suggests that, controlling for size, book-to-market ratio and momentum, analysts' forecasts are still more biased for equity issuers than for debt issuers.

In Panels C and D, we present the raw and benchmark-adjusted LTGFEs for capital distributing firms (NF < 0). There appears to be no clear relation between ER and LTGFEs among the capital distributing firms. This is consistent with our findings in Sections 3 and 4 about the relation between ER and future stock returns among capital distributing firms.

6. Aggregate data

Our analyses on earnings announcement returns, year-ahead stock returns and analysts' forecasts of firms' long term growth rates suggest that managers tend to issue more equities relative to debt when their firms are more overvalued by the market. We argue that BCGW (2010) finds no evidence for market timing because of a confounding new growth options effect in the data. The same argument helps to explain the controversy surrounding aggregate market timing. Baker and Wurgler (2000) find that equity share in new issues, an aggregate market timing variable constructed in the same sprit as the equity ratio in this paper, has predictive power for future stock market returns. Consistent with the market timing hypothesis, they find that there is a negative relation between equity share in new issues and future aggregate market returns. BCGW (2010) replicate Baker and Wurgler's (2006) tests and find the negative relation between equity share in new issues and future stock returns holds only for the sample period before 1997. When they include years after 1997 into the sample, the relation between future stock market return and equity share in new issues becomes statistically insignificant. They thus conclude that Baker and Wugler's (2006) findings may be specific to the data sample period before 1997.

One possible reason why equity share in new issues loses its predictive power after including the most recent data into the sample is that the confounding investment-in-growth-options effect has turned stronger over the years. Figure 1.1 plots the fraction of high R&D firms,

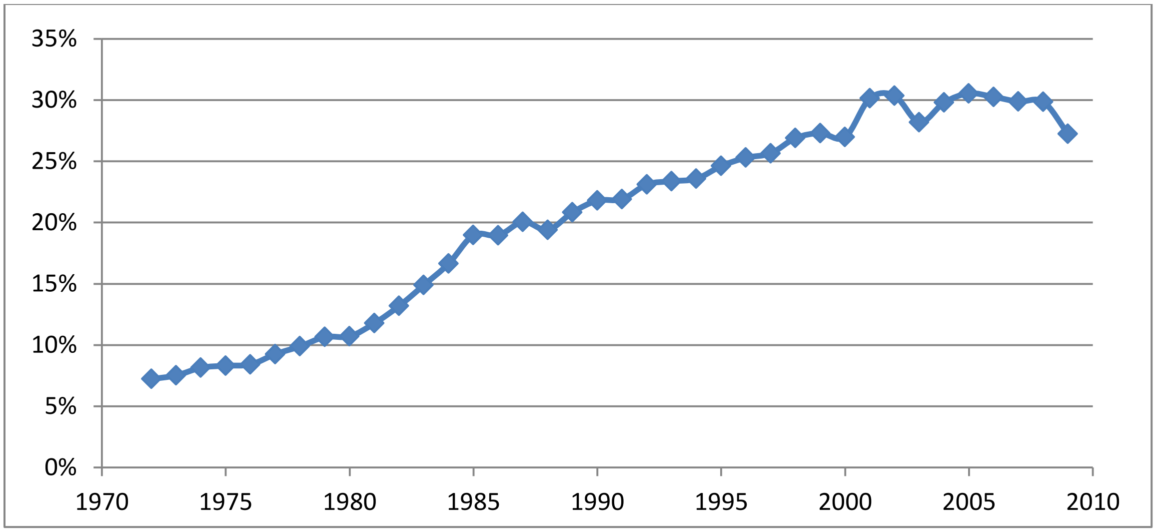

Figure 1.1. Fraction of high R&D firms in the sample

This figure plots the fraction of firms with high R&D spending over the years. Firms with R&D spending higher than 5% of lagged assets is defined as a high R&D firm.

defined as firms with R&D spending higher than 5% of lagged assets, in our sample. In 1972, only about 7% of the firms in our sample are classified as high R&D firms. The fraction has grown steadily over the years. By 2008, about 30% of the firms in our sample have R&D expenditure higher than 5% of lagged assets. Since high R&D firms are more likely to invest in new growth options, the trend in Figure 1.1 suggests that the confounding effect should have turned stronger over the years. Without controlling for this confounding effect, the predictive power of the equity issue in new issues will become weaker over the sample period. Since the fraction of high R&D firms are highest for years after 1997, it is not surprising that the negative relation between the equity issue in new issues and future stock market return disappears when the later years are included in the sample.

7. Conclusion

In this paper, we examine whether the debt-equity composition of net external financing predicts future stock returns. We find firms issuing more equity relative to debt tend to have lower earnings announcement returns in the subsequent year. The effect still exists after controlling for the level of external financing and firm characteristics that are known to affect cross-sectional stock returns. The evidence is more consistent with the mispricing hypothesis than with the investment based explanations for financing anomalies.

Then we investigate why previous research finds that there is no relation between the composition of external financing and future stock returns after controlling for the level of external financing. We hypothesize that there is a confounding investment-in-growth-options effect that offsets the market timing effect in the data. That is, firms are more likely to use equity to finance their investment in new growth options. By real options theory, the investment in growth options can cause an increase in the firms' required rates of return. This can potentially offsets the market timing effect related to firms' debt-equity choices. Consistent with this hypothesis, we find a negative relation between equity ratio and year-ahead stock returns after controlling for the new growth options effect. In addition, we examine the relation between firms' debt-equity choices and analysts' forecasts of firms' long term growth rates. We find analysts' forecasts are systematically more overoptimistic for heavy equity issuers than heavy debt issuers. This provides further support for the mispricing hypothesis.

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CHAPTER II

A NEW APPROACH FOR EVALUATING CAPITAL STRUCTURE DETERMINANTS

1. Introduction

The major theories of capital structure suggest that firms base their financing decisions on various cost-benefit considerations. The static-tradeoff theory predicts that the optimal leverage ratio reflects a tradeoff between the cost of bankruptcy and the value of the tax shield associated with interest deductions. The pecking order explanation of Myers and Majluff (1984) suggests that firms prefer internal to external financing and debt to equity financing due to concerns over adverse selection costs. Agency theory implies that a similar financing hierarchy can reduce the agency costs associated with the free cash flow problem. Since firms with different characteristics face different costs and benefits of debt financing, the theories imply that relations exist between firms' leverage and various firm characteristics. The empirical literature has identified a large number of capital structure determinants. Frank and Goyal (2009) re-examine previously identified variables and find that six leverage factors explain about 30% of the variation in firm leverage ratios.

As capital structure determinants evolve over time, changes in the costs and benefits of debt financing are likely to occur. Therefore, it is reasonable to expect time-series variation in capital structure determinants to have an impact on firms' debt ratios. This is a popular assumption in capital structure studies. For example, the popular partial adjustment model explicitly treats target leverage as a function of firm characteristics and then estimates the speed of adjustment toward the target (Hovakimia, Opler and Titman, 2001, Fama and French, 2002, Kayhan and Titman, 2007, Flannery and Rangan, 2006).

However, recent evidence documented in Lemmon, Roberts and Zender (2008) casts doubt on the importance of the previously identified determinants. They find that pooled OLS regressions using previously known determinants can only explain 18% - 29% of the variation in firm leverage ratios, whereas models with firm fixed effects can explain as much as 60%. Since firm fixed effects are included to capture unobserved, time-invariant heterogeneity, they conclude that "the majority of the variation in leverage is time invariant and largely unexplained by previously identified capital structure determinants". They also interpret their findings as evidence that firms rebalance toward time-invariant leverage targets[16].

These findings are interesting yet puzzling. In particular, one of the samples they use is a "Survivor" sample, which consists of firms with more than twenty years of non-missing data. Over the twenty year plus period, many firms experience nontrivial changes in firm characteristics. Since these changes involve factors associated with changes in the costs and benefits of debt financing, it is puzzling why such changes have only minimal effects on the time series variation of firms' leverage ratios[17].

The standard fixed effect model in finance controls for firm-specific heterogeneity by allowing firms to have heterogeneous intercepts. However, this model ignores the possibility that some slope coefficients can also be heterogeneous. Yet, it is likely that the marginal effects of some of these factors can vary across firms for at least two reasons. First, some leverage determinants, such as accounting ratios, are imperfect proxies for the underlying economic factors. Because firms differ in their accounting practices and/or in the nature of their assets, the same unit of change in an accounting variable can have different economic implications for different firms. Consequently, firms are likely to respond differently. For example, in response to an

[16] Their findings are inconsistent with the capital structure irrelevance argument because there is no reason for firms to stick to a particular leverage level over extended periods if capital structure is irrelevant.

[17] Based on firms' time series ranges in leverage, DeAngelo and Roll (2011) argue that capital structure stability is virtually always a temporary phenomenon. A potential concern over their evidence is that ranges in leverage could be affected by the general shift away from debt conservatism since the 1950s and by temporary, extreme fluctuations in debt ratios.

increase in firm size, firms that routinely use off-balance-sheet financing may adjust their capital structures by changing the amount of their operating leasing obligations, which has no direct effect on leverage as it is conventionally defined. Second, the marginal effects of the capital structure determinants may be conditional on other factors. Meyers (2003) suggests that capital structure theories are conditional theories. Each works better in some conditions than others. Some of the conditional factors can be unobservable. For example, management style (Bertrand and Scholar, 2003), financing friction and creditor relations may all affect how firms respond to the changes in the capital structure determinants of leverage. Furthermore, the marginal effects of a determinant can be conditional on other known determinants. For example, firms with more tangible assets have more attractive collateral to reassure lenders. Thus, an incremental change in total assets of such firms is likely to have higher marginal effects on their debt capacity and capital structure. In other words, there can be interaction effects between total assets and asset tangibility, which is illustrated by our example.

In this paper, we show that the puzzle documented by Lemmon, Roberts and Zender (2008) can be explained by the implicit assumption of a homogenous slope for leverage determinants. We show that the fixed effect model can produce "pseudo fixed effects" when they are used with data generating from firms that are characterized by heterogeneous slopes. Such fixed effects are "pseudo" in the sense that they are mechanical effects caused by neglecting slope heterogeneity. They exist even in situations where the variation in leverage is driven completely by the changes in capital structure determinants. Moreover, citing Pesaran and Smith (1995), we show that the fixed coefficient models can underestimate the effects of the capital structure determinants in the partial adjustment model. Therefore, the evidence in Lemmon, Roberts and Zender (2008) does not necessarily mean that target leverage ratios are time invariant, nor does it necessarily imply that leverage changes are better explained by firm fixed effects than by previously identified leverage determinants.

For this alternative explanation to be convincing, we need to uncover evidence that the data generating process for firm leverage ratios is indeed characterized by heterogeneous slope coefficients. One straightforward way to obtain such evidence is to run a horse race between a heterogeneous coefficient model and a fixed effect model. However, the application of the heterogeneous coefficient models requires a relatively long time series for each firm, causing potential concerns over survivorship bias. We address the problem by taking two approaches, one based on the full sample of firms and the other based on a Survivor sample. We estimate conventional regression models to the general sample and heterogeneous coefficient models to the Survivor sample. There are two advantages to studying the long time series in the Survivor sample. First, because there are longer time series for each sample firm, we can investigate to what extent the variation in firms' leverage is explained by the time-series variation in capital structure determinants. In this sense, the sample is comparable to the Survivor sample used by Lemmon, Robert and Zenders (2008). Second, the Survivor sample allows us to run a horse race between the fixed effect model and heterogeneous coefficient model. We study the general sample mainly to show that slope heterogeneity exists generally among firms.

Let's start from the evidence from the Survivor sample. Using the $\tilde{\Delta}$ test recently developed by Pesaran and Yamagata (2008), we formally test and reject the hypothesis of slope homogeneity. We thus conclude that the heterogeneity in the marginal effects of some leverage determinants is a credible alternative model for testing the determinants of firm leverage ratios.

To develop a more reliable assessment of the importance of capital structure determinants, we estimate models of leverage using heterogeneous coefficient methods. Following Hsiao (2003), we account for slope heterogeneity by running separate OLS regressions for each firm and by fitting random coefficient and/or multilevel regressions, with more focus on the latter method. The random coefficient model allows the slopes of leverage models to vary randomly across firms. The multilevel model allows the slopes of leverage models to vary by firm characteristics. We find that the heterogeneous coefficient models explain more variation in leverage than the fixed effect model. Specifically, the random coefficient models have adjusted R^2 statistics above 0.7. Moreover, the random coefficient model with heterogeneous slopes, but a homogeneous intercept has an adjusted R^2 of 0.7245, whereas the model with both heterogeneous intercepts and heterogeneous slopes has an adjusted R^2 of 0.7163. Therefore, when heterogeneous slopes are specified for the capital structure determinants, adding heterogeneous intercepts to the model has only minimal effects on model fit. To address concerns about model over-fitting, we compare the out-of-sample predictive performances of the two models. The random coefficient models consistently outperform the LSDV (least square dummy variable) and fixed effect models in terms of mean squared forecasting errors (MSE). Overall, the models' goodness of fit statistics suggest that the firm-specific heterogeneity in leverage determinants is better modeled by heterogeneous slopes than by heterogeneous intercepts, at least for firms in the Survivor sample. In other words, it is more appropriate to view firms as having heterogeneous responses to changes in capital structure determinants than to view firms as having time-invariant firm-specific leverage ratios (i.e., the firm fixed effects model). This conclusion is inconsistent with the commonly held view that firm leverage targets are time invariant.

The results from the Survivor sample suggest that slope heterogeneity can be a relevant explanation for the findings of Lemmon, Roberts and Zender (2008). For the general sample, we focus on the following two issues. First, we want to show that there is also substantial slope heterogeneity in the general sample. Second, we examine whether the cross-sectional differences in slopes are related to economically meaningful factors. We first examine the relation between slope heterogeneity and firm characteristics. As previously explained, a firm's slope coefficients can be affected by various observable and unobservable factors. Our goal is not to identify all such factors, but simply to show that slope heterogeneity is related to meaningful economic factors.

We find the slope heterogeneity in leverage models are related to the long term components of several slope determinants, such as firm size, profitability, MV/BV, tangibility and earnings volatility. The statistically significant relations that we identify suggest that financial constraints can play a role in determining slope heterogeneity. For example, firms with lower tangibility and firms with higher earnings volatility may face more financial constraints because they are associated with more information asymmetry from the investors' perspective. We find these firms are less sensitive to most capital structure determinants. Meyer's (2003) argument about the conditional applicability of the pecking order theory could also explain the cross-sectional differences in slope coefficients. For example, we find that larger firms and firms with fewer growth opportunities, higher profitability or more stable cash flows are more sensitive to the changes in profitability. This is consistent with his argument that "cash cows" face the greatest pressure to follow the pecking order. Moreover, we achieve meaningful improvements in adjusted R^2 when we allow the slope coefficients in the leverage models to vary with the long term components of these variables. These results suggest that the cross-sectional heterogeneity in slope coefficients is related to meaningful economic factors and can be explained by existing theories. It is unlikely that the slope heterogeneity in leverage models is merely a statistical artifact.

Finally, we examine the slope heterogeneity across industries. We estimate the leverage models separately for each industry with more than 200 observations and report the distribution of the coefficients across firms. We find substantial cross industry heterogeneity in slopes. For example, the profitability coefficient is – 0.6161 at the 20% percentile and – 0.1525 at the 80% percentile. Thus, the industries at the 20% percentile are almost four times more sensitive to the variation in internal cash flows than those at the 80% percentile. The substantial cross industry slope heterogeneity provides further evidence that slope homogeneity is an unlikely to be a descriptively valid assumption for target leverage ratios. Moreover, we find we can substantially improve on the OLS model's fit by allowing the coefficients of the leverage models to vary by industry and firm characteristics. This provides further evidence that the slope heterogeneity in the leverage models is related to economically meaningful firm and industry factors. In addition, we find adding industry-specific intercepts adds remarkably little to the model fit when heterogeneous slopes are specified for different industries. In contrast, even when the model includes industry fixed effects, meaningful improvements in adjusted R^2 can still be achieved by allowing industry-specific slopes. This indicates that firms in the same industry do share similarities in their capital structure decisions. However, such similarities are reflected not so much by a specific level of leverage that the industry is associated with as it is by how firms in the industry respond to changes in capital structure determinants.

The rest of the paper proceeds as follows. Section 2 discusses how the neglected slope heterogeneity can cause “pseudo fixed effects”. Section 3 introduces the estimation methods for heterogeneous panels, which will be used on the Survivor sample in Section 5. Section 4 describes the data. Section 5 presents the evidence from the Survivor sample. Section 6 provides the evidence from the general sample. Section 7 concludes.

2. “Pseudo Fixed Effects”

Existing capital structure studies control for firm-specific heterogeneity by allowing firms to have heterogeneous intercepts in their models. However, firm-specific heterogeneity can also be reflected in heterogeneous slope coefficients. In this section, we illustrate that alternative interpretations are possible for Lemmon, Robert and Zender’s (2008) findings when the leverage models are characterized with heterogeneous slopes.

When different firms have different coefficients for the capital structure determinants, the data generating process for leverage can be represented by equations (1) and (2).

$$L_{i,t} = \sum_{k=1}^{k} \beta_{k,i} x_{k,i,t-1} + u_{i,t} \tag{1}$$

$$\beta_{k,i} = \beta_k + \gamma_{k,i} \tag{2}$$

where $L_{i,t}$ is the leverage of firm i at time t and $x_{k,i,t-1}$ the kth capital structure determinant for firm i. In equation (2), β_k is the average effect across firms and $\gamma_{k,i}$ the firm-specific deviation from β_k. Substitute equation (1) into equation (2), we obtain

$$L_{i,t} = \sum_{k=1}^{K} \beta_k x_{k,i,t-1} + \sum_{k=1}^{K} \gamma_{k,i} x_{k,i,t-1} + u_{i,t} \tag{3}$$

$$= \sum_{k=1}^{K} \beta_k x_{k,i,t-1} + \underbrace{\underbrace{\sum_{k=1}^{K} \gamma_{k,i} \bar{x}_{k,i}}_{a_i} + \sum_{k=1}^{K} \gamma_{k,i} \ddot{x}_{k,i,t-1} + u_{i,t}}_{\varepsilon_{i,t}} \tag{4}$$

where $\bar{x}_{k,i}$ is the time-series mean of $x_{k,i,t-1}$ for firm i and $\ddot{x}_{k,i,t-1}$ the deviation from $\bar{x}_{k,i}$.

The existing research in capital structure uses econometric methods that assume homogeneous slopes, such as the pooled OLS regression, the least square dummy variable (LSDV) regression or the fixed effect model. When equation (4) is estimated using the pooled OLS method, the last three terms in the equation become the error term $\varepsilon_{i,t}$. When the model is estimated using the LSDV method or the fixed effect method, the $\sum_{k=1}^{K} \gamma_{k,i} \bar{x}_{k,i}$ term is effectively a "fixed effect". Notice that the model in equations (1) and (2) contains no firm-specific intercepts. Equation (4) shows that the "pseudo fixed effect" a_i can arise even if the variation in leverage is driven solely by the time series variation in the capital structure determinants. Therefore, the presence of firm fixed effects does not necessarily mean that the time-series variation of the capital structure determinants is unimportant. Nor do they necessarily imply that firms' leverage targets are time invariant.

The neglect of slope heterogeneity can be one of the reasons why the adjustment speeds estimated using fixed effect models are insensitive to the inclusion of the capital structure determinants (Lemmon, Roberts and Zender, 2008). Under the assumption of slope heterogeneity, the partial adjustment model can be represented by equations (5) - (7).

$$L_{i,t} = \lambda_i L_{i,t-1} + \sum_{k=1}^{K} \beta_{k,i} x_{k,i,t-1} + u_{i,t} \tag{5}$$

$$\lambda_i = \lambda + \eta_i \tag{6}$$

$$\beta_{i,k} = \beta_k + \gamma_{i,k} \tag{7}$$

In equations (6) and (7), λ and β_k are the average effects across firms and η_i and $\gamma_{k,i}$ the individual deviation from λ and β_k. Substituting equations (6) and (7) into equation (5) and rearranging terms, we obtain

$$L_{i,t} = \lambda L_{i,t-1} + \sum_{k=1}^{K} \beta_k x_{k,i,t-1} + (\underbrace{\eta_i L_{i,t-1} + \sum_{k=1}^{K} \gamma_{k,i} x_{k,i,t-1} + u_{i,t}}_{\varepsilon_{i,t}}) \tag{8}$$

The existing research interprets $1 - \lambda$ as the average capital structure adjustment speed. If equation (8) is estimated using a model with homogeneous slopes, the $\eta_i L_{i,t-1}$ and $\sum_{k=1}^{K} \gamma_{k,i} x_{k,i,t-1}$ terms enter into the error term $\varepsilon_{i,t}$. Pesaran and Smith (1995) point out there are three problems associated with the error term $\varepsilon_{i,t}$. First, the correlation between $L_{i,t-1}$ and $u_{i,t}$ causes what is often known as the short panel bias. Previous research in capital structure addresses the problem using various instrument variable methods (Flannary and Hankins, 2007, Lemmon, Roberts, Zender, 2008, Huang and Ritter, 2007). Second, the serial correlations in $\eta_i L_{i,t-1}$ and $\sum_{k=1}^{K} \gamma_{k,i} x_{k,i,t-1}$ induce the serial correlation in the error terms. Third, due to the presence of the $\eta_i L_{i,t-1}$ and $\sum_{k=1}^{K} \gamma_{k,i} x_{k,i,t-1}$ terms, the error term is contemporaneously correlated with the regressors. Consequently, the models assuming homogeneous coefficients will produce inconsistent estimates of λ and β_k. It is unlikely that the problem can be solved with instrument variable methods. To be a valid instrument, a variable must be correlated with $L_{i,t-1}$ and/or $x_{k,i,t-1}$. However, because $\eta_i L_{i,t-1}$ and $\gamma_{k,i} x_{k,i,t-1}$ are components of $\varepsilon_{i,t}$, any such variable will be correlated with $\varepsilon_{i,t}$, rendering them invalid instruments.

Pesaran and Smith (1995) derive the signs of the biases for the homogeneous coefficient model estimates of $\widehat{\lambda}$ and $\widehat{\beta_k}$. They show that $\widehat{\lambda}$ will be biased toward one when $x_{k,i,t-1}$ has positive autocorrelation. $\widehat{\beta_k}$ will be biased toward zero regardless of the autocorrelation structure of $x_{k,i,t-1}$. When $\widehat{\beta_k}$ is biased toward zero, the homogeneous coefficient models underestimate the effects of the capital structure determinants. In other words, the homogeneous coefficient models fail to adequately account for the changes in leverage targets that are caused by the changes in the determinants. They overestimate the effect of the lagged leverage and underestimate the effects of the capital structure determinants. This can partially explain why the adjustment speed changes little before and after including the capital structure determinants into the fixed effect models (Lemmon, Roberts and Zender, 2008).

So far we have demonstrated that the neglected slope heterogeneity can explain the findings documented by Lemmon, Roberts and Zender (2008). For this explanation to be relevant, we need the evidence that the data generating process for firms' leverage is indeed characterized with heterogeneous slope coefficients. We will formally test the assumption of slope homogeneity in Section 5.

3. Estimation methods for heterogeneous panels

This section introduces the econometric methods for estimating heterogeneous panel models. For many applications in finance, the heterogeneous panel methods are unnecessary even when the data generating processes are characterized with heterogeneous slopes. This is because financial economists are mainly interested in the average effects. As shown by Zellner (1969), the homogeneous coefficient models can produce consistent estimates of the average effects as long as the regressors are exogenous and the slopes differ randomly across groups. However, the average effects are not the sole concern in this paper. In this paper, we are interested in assessing the percentage of variation in leverage that are explained by the capital structure determinants. To draw conclusions about whether the target leverage is time invariant, we also need evidence about whether the heterogeneous slopes assumption is more appropriate than the heterogeneous intercepts assumptions.

Heterogeneous panel models can be estimated using either Bayesian approaches or classic approaches. Classic approaches involve estimating separate OLS regressions for each firm (Pesaran and Smith, 1995, Hsiao, 2003) or estimating random coefficient/multilevel models[18]. I will focus more on the latter in this paper.

For convenience, the models in equations (1) – (2) are rewritten as

$$L_i = Z_i\theta_i + u_i \tag{9}$$

$$\theta_i = \theta + \gamma_i \tag{10}$$

In equations (9) and (10), θ_i is the vector of coefficients for the capital structure determinants, L_i the vector of leverage for firm i and Z_i the data matrix of capital structure determinants. The firm-specific components γ_i are assumed to have zero means and constant covariance Δ. The error term u_i is assumed to be normally distributed with mean zero and variance σ_i^2. Substitute equation (9) into equation (10), we obtain

$$L_i = Z_i\theta + Z_i\gamma_i + u_i \tag{11}$$

Swamy (1970) shows that θ can be estimated using the generalized least square estimator

$$\hat{\theta} = \left(\sum_{i=1}^{N} Z_i^{'} \Phi_i^{-1} Z_i\right)^{-1} \left(\sum_{i=1}^{N} Z_i^{'} \Phi_i^{-1} L_i\right) \tag{12}$$

[18] In standard financial econometrics, the fixed (random) effect refers to the firm-specific intercepts that are correlated (uncorrelated) with the regressors. In the random coefficient/multilevel models literature, the fixed effect refers to a parameter (either an intercept or a slope coefficient) that is assumed to be constant and random effect a parameter that varies randomly across firms or over time. In this paper, the term *fixed effect* takes the meaning as in standard financial econometrics. When we discuss the random coefficient/multilevel models, we will refer to constant parameters explicitly as *homogenous intercepts* or *homogeneous (slope) coefficients* and random parameters explicitly as *heterogeneous intercepts* or *heterogeneous (slope) coefficients*.

where the covariance matrix Φ_i equals $Z_i \bigtriangleup Z_i^{'} + \sigma_i^2 I_T$. The best linear unbiased estimator for the firm-specific coefficient vector θ_i (Hsiao, 2003) is

$$\hat{\theta}_i = \hat{\theta} + \bigtriangleup Z_i^{'} \Phi_i^{-1}\left(L_i - Z_i\hat{\theta}\right) \tag{13}$$

The estimators in equations (12) and (13) are infeasible because the variance components are unobservable in practice. Therefore, we need to estimate the variance components in a first-stage estimation and then substitute the resulting estimates into equations (12) and (13) to obtain $\hat{\theta}$ and $\hat{\theta}_i$in a second stage. The existing random coefficient models differ mainly in how the variance components are estimated. In this paper, we use the likelihood based approach (Pinheiro and Bates, 2000)[19], which has been shown to be more accurate than the classic Swamy-Hsiao random coefficient model (Beck and Katz, 2006).

If the firm-specific coefficients are correlated with the regressors, the GLS estimator of the mean coefficient vector can be biased (Mundlak, 1978, Hsiao, 2003). We address this concern using two different methods. First, we estimate the random coefficient models using demeaned data. From equation (3), the model for demeaned data can be written as

$$\ddot{L}_{i,t} = \sum_{k=1}^{K} \beta_k \ddot{x}_{k,i,t-1} + \sum_{k=1}^{K} \gamma_{k,i} \ddot{x}_{k,i,t-1} + u_{i,t} \tag{14}$$

where $\ddot{L}_{i,t}$ and $\ddot{x}_{k,i,t-1}$ are the deviations from the time-series means for each firm. From equation (14), it is clear that β_k and $\gamma_{k,i}$ also can be estimated from the demeaned data. Since the firm-specific means are subtracted from the variables in equation (14), the correlation between the firm-specific $\gamma_{k,i}$ and the regressors is not an issue. Second, following Mundlak (1978) and Hsiao (2003), we estimate equation (11) along with auxiliary equations for the coefficient vector γ_i as a function of the ith firm's observed explanatory variables. Specifically, the following equation is specified for the firm-specific slope $\gamma_{k,i}$ in equation (3).

$$\gamma_{k,i} = \sum_{j=1}^{J} \eta_{k,j} \bar{x}_{j,i} + \xi_{1,i} \tag{15}$$

[19] We implement the model using SAS proc mixed procedure.

In equation (15), $\bar{x}_{j,i}$ is the firm-specific time series mean of the explanatory variable $x_{j,i}$. Equation (15) can then be substituted into equation (3) to obtain the reduced form model. The resulting model contains both the original explanatory variables and the interaction terms between the explanatory variables and time series means. Some econometricians view the resulting model as a special class of the random coefficient model. Others call such models multilevel models. For convenience, we call it a multilevel model. More details about the multilevel model can be found in Section 5.

4. Data and descriptive statistics

For the general sample, we start from all non-financial (SIC codes 6000 – 6999), non-utilities (SIC codes 4900 – 4999) companies in the annual Compustat Xpressfeed database between 1970 and 2007. We require that sample firms have positive assets and sales. Observations with missing data for market leverage or any of the variables in the regression models are deleted. Following previous research, we omit observations with leverage below 0 or above 1 and truncate relevant ratios at 1% and 99%. In addition, we require that the sample observations have non-missing values for the variables in the regression models. Because time series means of the variables are used in part of the analysis, we require that sample firms have at least five years of data. Time series means are less meaningful when the time series is less than five years. The actual data used for the regression models are chosen from this general sample and may vary from test to test. For example, when we estimate industry-specific regressions, we require that the sample firms be in industries with at least 200 observations. We will explain the necessary details when we discuss the specific tests. The Survivor sample is similarly constructed, except that the sample firms must have 20 years of data between 1988 and 2007.

Table 2.1 presents the descriptive statistics for the sample companies. The reported variables include book leverage, market leverage and various capital structure determinants. The market leverage is the ratio of total debt over the sum of debt and market value of equity. Book

Table 2.1. Descriptive statistics

The table reports the descriptive statistics for our samples. The Survivor sample consists of 894 non-financial, non-utility US companies with 20 years of data between 1998 and 2007. The general sample consists of 10391 non-financial, non-utility US companies with at least five years of data between 1970 and 2008. Market leverage is the ratio of total debt to the sum of total debt and market value of equity. Book leverage is the ratio of total debt to the book value of assets. Assets are deflated using 2000 as the base year. MV/BV is the ratio of the market value of assets to the book value of assets. Profitability is operating income scaled by book assets. Median industry leverage is the median market leverage for each three digit SIC industry. Earnings volatility is the rolling 10 year standard deviations of profitability. We require minimum three years of data to calculate earnings volatility. T bill is the return on 6 month T bill.

	Survivor		General	
	Mean	Median	Mean	Median
Market leverage	0.2239	0.1684	0.2746	0.2143
Book leverage	0.2192	0.2084	0.2414	0.2197
Assets	4782	388	1555	71
Profitability	0.0782	0.0879	0.0361	0.0764
MV/BV	1.6934	1.3974	1.7398	1.2801
Tangibility	0.3032	0.2604	0.3174	0.2678
Industry median leverage	0.1944	0.1785	0.2211	0.2017
Earnings volatility	0.0608	0.0425	0.1032	0.0563
Dividend	0.6249	1	0.4943	0
T bill	0.0443	0.0482	0.0548	0.0524
Firm	894		10391	
N	17880		140120	

leverage is the ratio of total debt to the book value of assets. MV/BV is the ratio of the market value of assets to the book value of assets. Profitability is operating income scaled by book assets. Median industry leverage is the median market leverage for each three digit SIC industry with more than three companies. Earnings volatility is the rolling 10 year standard deviation of profitability. We require a minimum of three years of operating income to calculate the earnings volatility variable. Dividend is a dummy variable that takes the value one if a firm pays dividend.

The six month T-bill, which is used as a proxy for expected inflation, is obtained from the Fed website. The Compustat definitions of the financial variables are provided in Appendix 2.1.

5. Evidence from the survivors sample

5.1 Test of Slope Homogeneity

For the explanation in Section 2 to be relevant, we need to determine whether slope heterogeneity is an appropriate assumption for the leverage models. For the Survivor sample, we check the appropriateness of the assumption using two different methods. First, we examine the variance of the firm-specific components $\gamma_{k,i}$ in equation (2). If the slope coefficients are heterogeneous across firms, the variances of $\gamma_{k,i}$ will be statistically different from zero. Specifically, we estimate the model in equations (1) and (2) using a random coefficient model and then re-estimate the model under the restriction that $\gamma_{k,i} = 0$. Based on the log likelihood statistics, we can test whether the variances of $\gamma_{k,i}$'s are statistically different from zero.

Second, we test the hypothesis of slope homogeneity, using the $\tilde{\Delta}$ test recently developed by Pesaran and Yamagata (2008). The $\tilde{\Delta}$ test explicitly tests the hypothesis of slope homogeneity. The test statistic is provided in Appendix 2.2.

In Table 2.2, we present the results of the likelihood ratio test and the $\tilde{\Delta}$ test. Both tests suggest that the hypothesis of slope homogeneity can be rejected at $p < 0.0001$. This is not surprising given the high degree of firm-specific heterogeneity in capital structure that has been documented in previous studies. In unreported analysis, we also drop or add capital structure determinants from the model one at a time and then test the hypothesis of slope homogeneity for the resulting models. The null hypothesis is rejected in all cases. Since the hypothesis of slope homogeneity is rejected, the explanation in Section 2 can at least partly explain Lemmon, Robert and Zender's (2008) findings.

Table 2.2. Test of Slope Homogeneity

The table reports the results of the likelihood ratio and the $\tilde{\Delta}$ tests in Section 5.1. The tests are performed on the non-financial, non-utility US companies with 20 years of data in Compustat between 1998 and 2007 to check whether the assumption of slope heterogeneity hold for the leverage model in equation (1). The dependent variable is market leverage. The regressors include size, profitability, MV/BV, tangibility, median industry leverage and inflation. The variable definitions are provided in Table 2.1.

	Δ statistic	p value
Likelihood ratio test	12547.43	< 0.0001
$\tilde{\Delta}$ test	50.4340	< 0.0001

5.2 How important are the capital structure determinants?

Lemmon, Roberts and Zender (2008) find that the fixed effect model can explain substantially more variation in leverage than the pooled OLS regressions. They argue that the majority of the variation in leverage is unexplained by previously identified determinants. However, due to the presence of “pseudo fixed effects”, the adjusted R^2 statistics of the pooled OLS and fixed effect models provide misleading information about the relative importance of capital structure determinants. In this subsection, we assess whether firm-specific attributes have incremental explanatory power under the maintained assumption of slope heterogeneity. We compare both the in-sample and the out-of-sample performances of the models.

5.2.1 Results from firm-specific regressions

We estimate separate OLS regressions for each firm. The regressors include the six core capital structure determinants identified by Frank and Goyal (2009): firm size, profitability, MV/BV, tangibility, industry median leverage and expected inflation as proxied by the return on six month T bill. Lemmon, Roberts and Zender (2008) use two other variables, earnings volatility and a dividend dummy. We do not include the dividend dummy because it is largely time invariant and thus can not be used in the firm-specific regressions. To calculate earnings volatility, we need at least three years of data on profitability. Since minimum data restrictions on profitability further restrict our sample size, we choose not to include it in the model. We nevertheless consider these two variables when we analyze the general sample.

The regression for each firm has six regressors and is estimated using twenty years of data. Because the sample size is small relative to the number of regressors, the estimation results are necessarily noisy. Despite this limitation, the firm-specific regression results provide a useful starting point because they do not utilize information in the cross-section and thus provide evidence about whether time series variation in the determinants of capital structure is important.

The estimation results are reported in Table 2.3. Panel A of Table 2.3 presents the mean group estimates of the coefficients for the capital structure determinants (Pesaran and Smith, 1995). The mean group estimator involves estimating firm-specific regressions and then averaging the coefficients across firms. The coefficients have signs and significance levels that are consistent with previous research. Therefore, even though the results for individual firm-specific regressions tend to be noisy, the mean coefficients of the 894 firm-specific regressions suggest that the model captures much of the underlying factors that determine capital structure decisions.

Panel B reports the distribution of adjusted R^2 statistics of the firm-specific regressions. In standard fixed effects specifications, firm fixed effects can be loosely interpreted as firm-specific intercepts. The adjusted R^2 of the firm-specific regressions then measures the incremental explanatory power of the capital structure determinants beyond an intercept only model. For about 5% of the firms, the adjusted R^2 is less than 0.0042. For these firms, capital structure determinants have little explanatory power beyond the intercepts. However, the 25 percentile, the 50 percentile and the 75 percentile of the adjusted R^2 statistics are respectively 0.2896, 0.5196 and 0.6932. Therefore, for most firms, the capital structure determinants explain a significant proportion of the variation that is unexplained by firm-specific intercepts.

Panel C evaluates the explanatory power of the capital structure determinants in the overall sample. The first column presents adjusted R^2 for a model that only estimates firm

Table 2.3. Results from Separate OLS Regressions by Firm

The table reports the estimation results of the firm-specific OLS regressions. The sample consists of the non-financial, non-utility US companies with 20 years of data between 1988 and 2007. Size is measured as the log of book assets. MV/BV is the ratio of the market value of assets to the book value of assets. Profitability is operating income scaled by book assets. Tangibility is net plant, property and equipment scaled by book assets. Industry median leverage is the median leverage for each three digit SIC industry. T bill is the return on six month T bill from the FED website. Except for T bill, all regressors are lagged one year. Panel A reports the coefficient estimates of the mean group model. To calculate the mean group estimates, we fit OLS regressions of equation (1) for each firm in the sample. The mean coefficients of the firm-specific OLS regressions are then taken as the coefficients for the mean group model. Standard errors are reported in the parentheses. Panel B reports the distribution of the adjusted R^2 statistics of the firm-specific OLS regressions. Panel C reports the adjusted R^2 statistics of the model with only firm dummies, the LSDV model and the model with firm-specific slopes for each firm. [a], [b] and [c] denotes statistically significant at 1%, 5% and 10%.

Panel A: Mean group estimates

	Intercept	Size	Profitability	MV/BV	Tangibility	Industry median leverage	T bill
Coef	-0.1731 [a]	0.0505 [a]	-0.1951 [a]	-0.0311 [a]	0.1497 [a]	0.3831 [a]	0.4055 [a]
Stderr	(0.0403)	(0.0053)	(0.0294)	(0.0046)	(0.0375)	(0.0333)	(0.0566)

Panel B: Distribution of adjusted R^2 of the firm-specific regressions

5%	10%	25%	50%	75%	90%	95%
0.0042	0.1126	0.2896	0.5196	0.6932	0.7948	0.8494

Panel C: Adjusted R^2 statistics of the model with only firm dummies, the LSDV model and the firm-specific regressions for the overall sample

	Dummy Only	LSDV	Firm-Specific OLS
Adjusted R^2	0.5562	0.6205	0.8002

dummies. The second and third columns present the statistics, respectively, for the LSDV model and the firm-specific regressions. Because the models differ in the number of parameters, it is more appropriate to use adjusted R^2, rather than R^2, to evaluate model fit. The dummy only model an adjusted R^2 of 0.5562. The adjusted R^2 of the LSDV model is 0.6205, which is only 0.064 higher than dummy only model. Since the adjusted R^2 indicates a marginally better fit relative to the dummy only model, it is not possible to rule out the possibility that the capital structure determinants are unimportant. However, as we show in equation (4), the effects of the capital structure determinants can be absorbed by firm fixed effects. The overall adjusted R^2 of firm-specific regressions is 0.8002. Therefore, when slope heterogeneity is properly accounted for, the capital structure determinants have substantially more explanatory power than what is suggested by the LSDV model.

Although the firm-specific regressions provide preliminary evidence about the importance of the capital structure determinants, there are two main concerns. First, the sample size is small relative to the number of regressors being estimated, the estimation results may not be stable. Second, firm-specific regressions ignore cross-sectional information. In response to these limitations, we examine whether more conclusive evidence can be obtained from the random coefficient/multilevel models, which utilize both time-series and cross-sectional information.

5.2.2 Results from Random coefficient/multilevel models

Table 2.4 reports the estimation results of the random coefficient/multilevel models. In Panel A, we compare the models estimated using the raw data. For the random coefficient/multilevel models, the table reports the average effects across firms, i.e., the $\hat{\theta}$ in equation (12). The firm-specific components are suppressed. The least square dummy variable (LSDV) model is used as the benchmark model. RCM I is a random coefficient model with

Table 2.4. Results from random coefficient models

The table compares the results of the least square dummy variable (LSDV) model with those of the random coefficient/multilevel models. The sample consists of the non-financial, non-utility US companies with 20 years of data between 1988 and 2007. The dependent variable is market leverage. Size is measured as the log of book assets. MV/BV is the ratio of the market value of assets to the book value of assets. Profitability is operating income scaled by book assets. Tangibility is net plant, property and equipment scaled by book assets. Industry median leverage is the median leverage for each two digit SIC industry. T bill is the return on six month T bill. Panel A reports the models estimated using the raw data. The RCM I model has homogeneous intercept yet heterogeneous slopes. The RCM II model has both heterogeneous intercepts and heterogeneous slopes. The MLM model is the multilevel model in equations (16) – (17). Panel B reports the models estimated after subtracting the firm-specific means from the data. For both Panel A and Panel B, the columns for the random coefficient/multilevel models report the average effects (β_k in equation (2)). The firm-specific slopes are suppressed. Standard errors are reported in the parentheses. [a], [b] and [c] denotes statistically significant at 1%, 5% and 10%.

Panel A: Models using raw data

	LSDV		RCM I		RCM II		MLM	
Intercept	-0.1259	a	0.0135	a	0.0314	a	-0.0235	a
	(0.0263)		(0.0075)		(0.0115)		(0.0088)	
Size	0.0289	a	0.0204	a	0.0191	a	0.0386	a
	(0.0013)		(0.0014)		(0.0016)		(0.0051)	
Profitability	-0.1926	a	-0.2069	a	-0.2185	a	-0.1565	a
	(0.0098)		(0.0164)		(0.0156)		(0.0747)	
MV/BV	-0.0189	a	-0.0244	a	-0.0253	a	-0.0248	a
	(0.0010)		(0.0015)		(0.0015)		(0.0063)	
Tangibility	0.1626	a	0.0850	a	0.0810	a	0.3254	a
	(0.0093)		(0.0143)		(0.0137)		(0.0674)	
Industry median leverage	0.2936	a	0.3155	a	0.3046	a	0.7136	a
	(0.0108)		(0.0180)		(0.0179)		(0.0849)	
T bill	0.6232	a	0.3563	a	0.3363	a	1.0409	a
	(0.0389)		(0.0401)		(0.0401)		(0.2338)	
Size$\times \overline{\text{Size}}$							-0.0008	
							(0.0005)	
Size $\times \overline{\text{Profitability}}$							-0.0164	
							(0.0159)	
Size $\times \overline{\text{MV/BV}}$							-0.0042	a
							(0.0015)	
Size $\times \overline{\text{Tang}}$							-0.0072	
							(0.0060)	
Size $\times \overline{\text{Indlev}}$							0.0293	b
							(0.0144)	
Profitability$\times \overline{\text{Size}}$							0.0080	
							(0.0095)	
Profitability$\times \overline{\text{Profitabilty}}$							-0.7390	a
							(0.2277)	
Profitability $\times \overline{\text{MV/BV}}$							0.0433	c
							(0.0244)	
Profitability $\times \overline{\text{Tang}}$							-0.0052	
							(0.1010)	
Profitability $\times \overline{\text{Indlev}}$							-0.6851	a

(Table 2.4. cont'd)

				(0.2576)	
MV/BV× $\overline{\text{Size}}$				-0.0030	a
				(0.0008)	
MV/BV× $\overline{\text{Profitabilty}}$				0.0609	a
				(0.0180)	
MV/BV× $\overline{\text{MV/BV}}$				0.0114	a
				(0.0018)	
MV/BV× $\overline{\text{Tang}}$				-0.0137	
				(0.0098)	
MV/BV× $\overline{\text{Indlev}}$				-0.1125	a
				(0.0246)	
Tang× $\overline{\text{Size}}$				-0.0175	b
				(0.0074)	
Tang × $\overline{\text{Profitability}}$				-0.1193	
				(0.2299)	
Tang × $\overline{\text{MV/BV}}$				-0.0525	b
				(0.0233)	
Tang × $\overline{\text{Tang}}$				0.0244	
				(0.0803)	
Tang × $\overline{\text{Indlev}}$				0.1481	
				(0.2147)	
Indlev× $\overline{\text{Size}}$				-0.0085	
				(0.0090)	
Indlev × $\overline{\text{Profitability}}$				-0.4735	
				(0.3345)	
Indlev × $\overline{\text{MV/BV}}$				-0.1601	a
				(0.0324)	
Indlev × $\overline{\text{Tang}}$				0.0546	
				(0.0966)	
Indlev × $\overline{\text{Indlev}}$				-0.2719	
				(0.2255)	
T bill× $\overline{\text{Size}}$				-0.1068	a
				(0.0265)	
Tbill × $\overline{\text{Profitability}}$				1.0626	
				(0.8357)	
T bill× $\overline{\text{MV/BV}}$				-0.0722	
				(0.0812)	
T bill× $\overline{\text{Tang}}$				-0.8312	a
				(0.2932)	
T bill× $\overline{\text{Indlev}}$				3.0735	a
				(0.7214)	
AIC	-30310	-36580	-37049	-36107	
BIC	-30302	-36474	-36910	-35823	
Adjusted R^2	0.6192	0.7245	0.7163	0.7064	

Panel B: Models using demeaned data

	Fixed Effect		RCM III	
Intercept	-0.0277		-0.0233	
	(0.0018)		(0.0016)	
Size	0.0289	a	0.0399	a
	(0.0012)		(0.0033)	
Profitability	-0.1925	a	-0.2177	a
	(0.0096)		(0.0189)	
MV/BV	-0.0189	a	-0.0250	a
	(0.0009)		(0.0019)	
Tangibility	0.1627	a	0.1461	a
	(0.0091)		(0.0206)	
Industry median leverage	0.2937	a	0.3381	a
	(0.0105)		(0.0211)	
Inflation	0.6223	a	0.5233	a
	(0.0378)		(0.0342)	
AIC (smaller is better)	-35689		-43276	
BIC (smaller is better)	-35682		-43232	
Adjusted R^2	0.1420		0.4520	

heterogeneous slopes but homogenous intercept. RCM II is a random coefficient model with both heterogeneous intercepts and coefficients. Based on the information criteria and the adjusted R^2 statistics[20], the models with heterogeneous slope coefficients outperform the LSDV model. The adjusted R^2 for RCM I and RCM II are, respectively, 0.7245 and 0.7163. The information criteria for these two models are also quite similar. Therefore, when heterogeneous slopes are specified for the capital structure determinants, adding heterogeneous intercepts to the model only marginally improves the model fit. This is consistent with equation (4), which suggests that the firm-specific intercepts in the leverage models can capture the pseudo fixed effects.

As mentioned in Section 3, a potential concern is that firm-specific slopes may be correlated with the regressors, rendering the estimators inconsistent (Mundlak, 1978, Hsiao,

[20] The adjusted R^2 is calculated as $1-\frac{\sum(L_{i,t}-\hat{L}_{i,t})^2}{\sum(L_{i,t}-\bar{L}_{i,t})^2}\frac{n-1}{n-p-1}$, where $\hat{L}_{i,t}$ is the fitted value calculated using the best linear unbiased predictor $\hat{\theta}_i$. We penalize the statistic for each firm-specific slope that is included in the model.

2003). We estimate the multilevel model (MLM) using equation (11) along with auxiliary equations for the coefficient vector γ_i as a function of the ith firm's observed explanatory variables. Specifically, the model can be written as

$$L_i = \beta_1 size_i + \beta_2 profit_i + \beta_3 MV/BV_i + \beta_4 tangibility_i + \beta_5 inustry\ median_i + \beta_6 inflation_i$$
$$+\gamma_{1,i} size_i + \gamma_{2,i} profit_i + \gamma_{3,i} MV/BV_i + \gamma_{4,i} tangibility_i + \gamma_{5,i} industry\ median_i + \gamma_{6,i} inflation_i$$
$$+ u_i \qquad (16)$$

and the auxiliary equations are, for k = 1 to 6,

$$\gamma_{k,i} = \eta_{1,k}\overline{size}_i + \eta_{2,k}\overline{profit}_i + \eta_{3,k}\overline{MV/BV}_i + \eta_{4,k}\overline{tangibility}_i + \eta_{5,k}\overline{industry\ median}_i + \xi_{1,i} \quad (17)$$

For convenience, the time scripts are suppressed in equation (16). In equation (17), bars denote the time-series means of the variables for each firm i. Substituting equation (17) into equation (16), we obtain a reduced form of the standard multlevel model, which includes the capital structure determinants and their interaction terms with $\overline{size}_i$, $\overline{profit}_i$, $\overline{MV/BV}_i$, $\overline{tangibility}_i$ and $\overline{industry\ median}_i$ as explanatory variables.

The last column in Panel A of Table 2.4 presents the estimation results for the MLM model. Some of the interaction terms have statistically significant coefficients, indicating that the firm-specific slopes are indeed related to the firm characteristics.

The main purpose of this section is to compare model fit. Since we include these interaction terms simply to control for possible correlation between capital structure determinants and firm-specific slopes, we choose not to discuss the coefficients of the interaction terms. We provide a more detailed discussion of these interaction terms when we analyze the general sample. In terms of information criteria and the adjusted R^2, MLM is similar to the two random coefficient models. Therefore, after controlling the correlation between the firm-specific slopes and the regressors, the model with heterogeneous slopes still explains more variation in leverage than the LSDV model does, but has similar within-sample explanatory power relative to the RCM I and RCM II models.

Rather than estimate firm-specific dummy variables, we estimate a standard fixed effect model using demeaned data as specified in equation (14). Panel B of Table 2.4 presents the models estimated using the demeaned data. We present the demeaned models in a different panel because the fit statistics of models using different data cannot be compared with each other. The model in the first column is an OLS model estimated using demeaned data, which is effectively a fixed effect model. RCM III is the random coefficient model in equation (14). Consistent with the results in Panel A, the random coefficient model outperforms the fixed effect model in terms of information criteria and adjusted R^2 ,providing further evidence that the capital structure determinants explain substantially more variation in leverage than what is suggested by the fixed effect model.

Given the large number of coefficients being estimated, the possibility of over-fitting is a potential concern. To address this, we compare the out-of-sample predictive performances of the different models. When over-fitting is a problem, the models exaggerate minor fluctuations in the data, leading to poor predictive performance. By contrast, the models that do the best job capturing the true economic relations are likely to perform better in out-of-sample predictive tests.

We use the MSE (mean squared forecasting error) ratio to compare the out-of-sample performance of the models over the one year, five year and eight year horizons. For the one year horizon, we first estimate a model using the nineteen years of data before a particular year. Then we plug the values of the capital structure determinants in the twentieth year into the fitted model to predict the firms' leverage. Specifically, we predict the leverage in 2003, 2004, 2005, 2006 and 2007 using the models fitted with the data in 1983 – 2002, 1984 – 2003, 1985 – 2004, 1987 – 2005 and 1988 - 2006. For the five year horizon, we estimate the model with data from 1988 – 2002. The forecast period is 2003 – 2007. For the eight year horizon, the model is fitted with data from 1988 to 1999 and the forecast period is 2000 – 2007. Once the forecasts are obtained, we calculate the MSEs of the models.

Panel A of Table 2.5 reports the MSE ratios for the one year horizon. The models in the first four columns correspond to the models in Panel A of Table 2.4. The models in the last two columns correspond to the models in Panel B of Table 2.4. For the models estimated using raw

Table 2.5. Out-of-Sample Prediction

The table compares the out-of-sample predictive performances of the models. Panel A, B and C report the mean squared forecasting error (MSE) ratios for the one year, five year and eight year horizons. The first four columns report the MSEs for the models estimated using the raw data and the last two columns for the models estimated using demeaned data. The LSDV model is the least square dummy variable (LSDV) model. The RCM I model has homogeneous intercept and heterogeneous slopes. The RCM II model has both heterogeneous intercepts and heterogeneous slopes. The MLM model is the multilevel model in equations (16) – (17). The RCM model for demeaned data has heterogeneous slopes. For the one year horizon, the models are fitted using the data in the previous nineteen years. The values of the capital structure determinants in the 20th year are then plugged into the fitted models to obtain the predicted leverage. For the five year horizon, the model is fitted using data from 1988 to 2002. The fitted parameters are then used to predict the leverage from 2003 to 2007. For the eight year horizon, the model is fitted using data from 1988 to 1999. The fitted parameters are then used to predict the leverage from 2000 to 2007. Based on the predicted leverage, the MSE ratios (model MSE/benchmark MSE) are then calculated. For the models estimated using the raw (demeaned) data, the MSE of the LSDV (fixed effect) model is used as the benchmark MSE.

Panel A: MSE ratio for one year horizon

	Raw Data				Demeaned Data	
Year	LSDV	RCM I	RCM II	MLM	Fixed Effect	RCM III
2003	1	0.6514	0.6240	0.6577	1	0.6158
2004	1	0.7008	0.7129	0.7083	1	0.7714
2005	1	0.7802	0.7529	0.7859	1	0.7564
2006	1	0.8270	0.7945	0.8322	1	0.7891
2007	1	0.7181	0.7026	0.7194	1	0.7054

Panel B: MSE ratio for five year horizon

	Raw Data				Demeaned Data	
Year	LSDV	RCM I	RCM II	MLM	Fixed Effect	RCM III
2003	1	0.6505	0.6387	0.6523	1	0.5911
2004	1	0.7986	0.8184	0.8116	1	0.7219
2005	1	0.9003	0.9182	0.9146	1	0.7886
2006	1	0.9904	1.0169	0.9999	1	0.8815
2007	1	0.9519	0.9886	0.9402	1	0.8671

Panel C: MSE ratio for the eight year horizon

	Raw Data				Demeaned Data	
Year	LSDV	RCM I	RCM II	MLM	Fixed Effect	RCM III
2000	1	0.8542	0.8195	0.8197	1	0.9076
2001	1	0.9114	0.8777	0.8582	1	0.8439
2002	1	0.8810	0.8853	0.8446	1	0.6656
2003	1	0.8913	0.9296	0.8715	1	0.6473
2004	1	0.8927	0.9353	0.8999	1	0.6788
2005	1	0.8714	0.8889	0.8934	1	0.7811
2006	1	0.9454	0.9523	0.9616	1	0.9113
2007	1	0.9354	0.9607	0.9228	1	0.8825

data, the MSE of the LSDV model is used as the benchmark MSE. For the models estimated using the demeaned data, the MSE of the fixed effect model is used as the benchmark MSE. The models exhibit consistent predictive performance. For the raw data models, the three random coefficient/multilevel models consistently outperform the LSDV model. The MSEs of the random coefficient/multilevel models are about 25% - 28% smaller than the benchmark model. Moreover, the MSEs for RCM I and RCM II are similar. Therefore, when heterogeneous slopes are specified for the capital structure determinants, allowing heterogeneous intercepts adds little to the predictive performance. This is inconsistent with the view that the target leverage is time invariant. For the demeaned data models, RCM III consistently outperforms the fixed effect model. The average MSE reduction is about 28%.

Panel B of Table 2.5 reports the MSE ratios for the five year horizon. As we mention in Section 2, firm-specific slopes are assumed to be invariant across time largely for modeling convenience. More realistically, we can view them as being stable, yet still slowly evolving time. As time elapses, the firm-specific slopes that are estimated during the estimation period become less accurate predictors for the firm-specific slopes during the forecast period. Thus, their advantage against the LSDV model will decrease over time. This appears to be true in Panel B. For the raw data, the random coefficient/multilevel models outperform the LSDV model in the first two – three years. For the demeaned data, the random coefficient model outperforms the fixed effect model in all five years, but their advantages get smaller over time. The results in Panel C also confirm the superior out-of-sample performances of the random coefficient/multilevel models over the eight year horizon.

Since the random coefficient models outperform the benchmark models in out-of-sample prediction, it is unlikely that their superior in-sample fit is merely a statistical artifact. The results from Table 2.4 and Table 2.5 suggest that the random coefficient models capture the underlying economic relationship better than the benchmark models do.

6. Evidence from the general sample

The results from the Survivor sample show that the capital structure determinants can explain substantially more variation in leverage when the models include proper controls for slope heterogeneity. This supports our view that slope heterogeneity can be a relevant explanation for the fixed effect puzzle documented by Lemmon, Roberts and Zender (2008). In this section, we examine the results from the general sample. In addition to providing further evidence of slope heterogeneity, we explore the potential sources of slope heterogeneity. Because many of the factors affecting firm-specific slopes are likely to be unobservable, we do not attempt to identify all sources of slope heterogeneity. Instead, we focus on the relation between slope heterogeneity and previously identified factors that are known to affect capital structure. The goal is to examine whether the differences in the firm-specific slopes are related to established economic factors.

6.1 Slope heterogeneity and firm characteristics

In this section, we examine the relation between slope heterogeneity and firm characteristics. We focus on five firm characteristics: firm size, profitability, MV/BV, tangibility and earnings volatility. There are several reasons why these variables could affect the firm-specific slope γ_i in equation (2). First and most importantly, these variables can be related to financial constraints. For example, Frank and Goyal (2009) argue that larger firms with low growth opportunities should find it relatively easy to raise external financing. They classify firms into constrained and unconstrained groups based on firm size and MV/BV. From a model selection perspective, they find that tangibility and firm size play a more important role in explaining leverage for low MV/BV firms. Similar arguments can also be made for firms with more tangible assets and lower earnings volatilities as they are associated with less information asymmetry. Finally, profitability is a component in the Whited and Wu (2006) and Kaplan and

Zingales Indices (1996) of financial constraints. When firms face higher financial constraints, they can be less responsive to changes in capital structure determinants because of higher adjustment costs.

Second, firms with larger size, higher profitability, more stable cash flows and fewer growth opportunities can be characterized as "cash cows". Myers (2003) suggests that such firms face more pressure to follow the pecking order. Similar predictions can be made from the agency theory perspective because stable cash cows benefit more from the discipline of regular interest payments. The conditional applicability of the capital structure theories can affect the cross-sectional differences in the firms' sensitivities toward the changes in capital structure determinants. For example, the conditional applicability of the pecking order theory suggests that firms with higher profitability or lower earnings volatility should follow the pecking order more closely and thus have more negative coefficient for profitability.

Similar reasoning allows us to develop additional predictions. For example, firms with higher tangibility have more collateralizable assets and thus can borrow more for a given amount of variation in firm size. This suggests that firms with more tangible assets should have more positive coefficients for size relative to other firms.

To examine how these variables affect the firms' slope coefficients in the leverage models, we estimate the model in equations (18) and (19).

$$L_{i,t} = (\beta_1 + \gamma_{1,i}) size_{i,t-1} + (\beta_2 + \gamma_{2,i}) profit_{i,t-1} + (\beta_3 + \gamma_{3,i}) \frac{MV}{BV}_{i,t-1} + (\beta_4 + \gamma_{4,i}) tangibility_{i,t-1} + (\beta_5 + \gamma_{5,i}) ind\ leverage_{i,t-1} + (\beta_6 + \gamma_{6,i}) earnings\ vol_{i,t-1} + \beta_7 dividend_{i,t-1} + u_{i,t-1} \quad (18)$$

For k = 1 to 6,

$$\gamma_{k,i} = \eta_{0,k} + \eta_{1,k}\overline{scaled\ size_i} + \eta_{2,k}\overline{profit_i} + \eta_{3,k}\overline{scaledMV/BV_i} + \eta_{4,k}\overline{tangibility_i} + \eta_{5,k}\overline{earnings\ vol_i} \quad (19)$$

Equation (18) includes the same capital structure determinants used in Lemmon, Roberts and Zender (2008). The β_k ' s are the average effect across firms. $\gamma_{m,i}$ ' s are the firm-specific slopes for firm i. Equation (19) specifies the firm-specific slopes $\gamma_{k,i}$ for each of the capital determinants, except for the dividend dummy, as a function of the long term components of the firms' size, profitability, MV/BV, tangibility and earnings volatility. We use firm-specific time series means as proxies for the long term components of these variables. For convenience, we will refer to the explanatory variables in equation (18) as capital structure determinants and those in equation (19) as *slope determinants*. In equation (19), firm size and MV/BV are scaled by the median of all NYSE companies that are in the Compustat for the same fiscal year. The scaling procedure is necessary because it controls for the possibility that inflation distorts the economic meaning of these variables. Moreover, even after controlling for inflation, time varying financial constraints still may result in estimates that reflect other time trends. For example, a firm that is valued at $10 billion in an expanding economy may find it easier to borrow funds than the same firm, also valued at $10 billion, in a recession.

We substitute equation (18) into equation (19) to obtain a reduced form version of the model. Due to space considerations, the details of the specification are presented in Appendix 2.3. Similar to our specification of the multilevel model in equations (16) and (17), the reduced form model contains the interaction terms between the capital structure determinants and the slope determinants.[21] If the slope determinants affect firm-specific slopes, many of the interaction terms will be statistically significant, and there should be meaningful improvement in model fit after including the interaction terms.

When there is substantial unobserved heterogeneity in equation (18) in addition to the slope heterogeneity specified in equation (19), the OLS estimation of equations (18) and (19) may be biased. To mitigate the effects of the unobserved heterogeneity, we also estimate a "fixed effect" version of the model by subtracting the firm-specific means from the variables in equation (18). The reduced form version of this model is specified as:

[21] Fama and French (2002) use similar interaction terms to accommodate the variation of adjustment speeds across firms.

$$\ddot{L}_{i,t} = (\beta_1 + \gamma_{1,i})\ddot{size}_{i,t-1} + (\beta_2 + \gamma_{2,i})\ddot{profit}_{i,t-1} + (\beta_3 + \gamma_{3,i})\ddot{MV/BV}_{i,t-1} + (\beta_4 + \gamma_{4,i})\ddot{tangibility}_{i,t-1}$$

$$+(\beta_5 + \gamma_{5,i})\ddot{ind\ leverage}_{i,t-1} + (\beta_6 + \gamma_{6,i})\ddot{earnings\ vol}_{i,t-1} + \beta_7 \ddot{dividend}_{i,t-1} + u_{i,t-1} \quad (20)$$

where $\ddot{x_{it}}$ denotes the deviation of variable x from its time series mean. We then estimate a reduced form of the model based on equations (19) and (20).

Estimation results are presented in Table 2.6. Panels A and B respectively report OLS estimation results for the reduced form models based on equations (18) and (19) and the "fixed effect" estimation results for equations (19) and (20). Given the large amount of unobserved heterogeneity that likely exists in leverage models, we consider the "fixed effect" estimation results to be more reliable. We present the OLS estimation results mainly to show the incremental improvement in adjusted R^2.

In Panel A of Table 2.6, Model I is an OLS model with the traditional capital structure determinants and year fixed effects. It is the base model for evaluating Model II, which is the "fixed effects" model as specified by equations (19) and (20). We present the interaction terms in Model II in separate columns. For example, the column $\times \overline{scaled\ size}$ presents the interaction terms between $\overline{scaled\ size}$ and the variables in the rows. Many of the interaction terms are statistically significant, supporting the view that the cross-sectional differences in the firms' slope coefficients relate to the variables in the column. Moreover, the adjusted R^2 is 0.3134 for the base model and 0.3939 for model II. Thus, allowing the firms' slopes to differ by the five slope determinants leads to meaningful improvements in model fit. The results in Panel A provide further evidence that part of the unobserved heterogeneity in the leverage models is related to the cross-sectional differences in slope coefficients and that the differences in slope coefficients are related to economically meaningful factors.

By way of comparison, almost all of the statistically significant OLS coefficients in Panel A remain significant and retain consistent signs in Panel B. However, some of the coefficient estimates for earnings volatility are no longer significant in the fixed effects model[22]. The interaction term between size and $\overline{profit_i}$ change signs and that between industry median leverage and $\overline{size_i}$ turns insignificant.

Given the substantial amount of unobserved heterogeneity that is known to exist in the leverage models, the "fixed effect" estimation in Panel B is more reliable. We will thus concentrate our discussion on Model II in Panel B. The interaction terms involving $\overline{scaled\ MV/BV_i}$, $\overline{tangibility_i}$ and $\overline{earnings\ vol_i}$ are broadly consistent with the view that financial constraints cause firms to be less responsive to changes in the capitals structure determinants. Take firms with higher $\overline{scaled\ MV/BV_i}$ for example. Consistent with Frank and Goyal (2009), we find that these firms are less responsive to the changes in size and tangibility. Moreover, the coefficients for profitability and MV/BV are less negative and the coefficient for industry median leverage is less positive. In other words, firms with relatively high growth opportunities are less sensitive to the changes in most of the capital structure determinants in the column. The firms with lower tangibility and higher earnings volatility may also face higher financial constraints due to greater information asymmetry. The results in Panel B show that these firms tend to be less sensitive to the changes in firm size, profitability, MV/BV and industry median leverage. Alternative explanations are possible for some of the interaction terms. For example, as mentioned earlier, the positive interaction between $\overline{earnings\ vol_i}$ and profitability is consistent with the pecking order or agency theory perspectives. Taken as a whole, the results regarding $\overline{scaled\ MV/BV_i}$, $\overline{tangibility_i}$ and $\overline{earnings\ vol_i}$ suggest that financial constraints play an important role in determining cross-sectional differences in slopes.

The results regarding the interaction terms involving $\overline{profit_i}$ are consistent with the argument that more profitable firms face more pressure to follow the pecking order (Meyers,

[22] The lack of significance of the earnings volatility variable may be due to the fact it is estimated on a rolling horizon basis, resulting in an estimate that is quite stable over time. Since most of the components are common, there will not be as much time series variation in the variable as the others included in equation (20).

Table 2.6. Regression models that allow slopes to vary with firm characteristics

This table presents the regression results of the models that allow slopes to vary with firm characteristics. The dependent variable is market leverage. The capital structure determinants are as defined in Section 4. The slope determinants are the firm-specific means of scaled size, profitability, scaled MV/BV, tangibility and earnings volatility. Scaled size and scaled MV/BV are, respectively, log(assets $_{t-1}$) and MV/BV scaled by the median of all NYSE companies in Compustat in the same fiscal year. Panel A presents the results for the OLS estimation of the model in equations (18) and (19). Panel B presents the results for the "fixed effect" estimation of the model in equations (19) and (20). The standard errors in the parentheses are clustered by firm. Year fixed effects are included. [a], [b], and [c] denote significant at 1%, 5% and 10%.

Panel A: Estimation results for the model in equations (18) and (19)

	Model I	Model II					
		Own effect	Interaction effects				
			$\times \overline{Scaled\ size}$	$\times \overline{Profit}$	$\times \overline{Scaled\ MV/BV}$	$\times \overline{Tangibility}$	$\times \overline{Earnings\ Vol}$
Intercept	0.2268[a]	0.0854[a]					
	(0.0074)	(0.0102)					
Size	0.0133[a]	0.0587[a]	-0.0119[a]	0.0127[a]	-0.0108[a]	0.0147[a]	-0.0069
	(0.0009)	(0.0028)	(0.0017)	(0.0040)	(0.0006)	(0.0028)	(0.0046)
Profitability	-0.1919[a]	-0.1667[a]	-0.3042[a]	-0.2274[a]	0.0566[a]	-0.0710[a]	0.0885[a]
	(0.0063)	(0.0207)	(0.0259)	(0.0258)	(0.0059)	(0.0274)	(0.0238)
MV/BV	-0.0453[a]	-0.0545[a]	-0.0048[b]	0.0008	0.0139[a]	-0.0147[a]	0.0160[a]
	(0.0008)	(0.0027)	(0.0025)	(0.0029)	(0.0006)	(0.0030)	(0.0026)
Tangibility	0.0671[a]	0.3464[a]	-0.1459[a]	0.0428	-0.0445[a]	-0.1847[a]	-0.0323
	(0.0070)	(0.0276)	(0.0219)	(0.0416)	(0.0092)	(0.0269)	(0.0438)
Earnings volatility	-0.0593[a]	0.0392	-0.1465[a]	0.0100	-0.0024	0.0135	0.0483[a]
	(0.0079)	(0.0320)	(0.0455)	(0.0314)	(0.0072)	(0.0351)	(0.0152)
Industry median leverage	0.5589[a]	1.0130[a]	-0.0182[a]	-1.4450[a]	-0.3181[a]	-0.0522	-0.4915[a]
	(0.0113)	(0.0329)	(0.0041)	(0.0953)	(0.0162)	(0.0394)	(0.1128)
Dividend dummy	-0.0469[a]	-0.0374[a]					
	0.0031	(0.0030)					
Year fixed effects	Yes	Yes					
N	140120				140093		
Adjusted R^2	0.3104				0.3939		

Table 2.6. (Cont'd)

Panel B: Estimation results for the model in equations (19) and (20)

	Model I	Model II					
		Own effect	Interaction effects				
			$\times \overline{Scaled\ size}$	$\times \overline{Profit}$	$\times \overline{Scaled\ MV/BV}$	$\times \overline{Tangibility}$	$\times \overline{Earnings\ Vol}$
Intercept	0.0666[a]	0.0696[a]					
	(0.0032)	(0.0032)					
Size	0.0262[a]	0.0443[a]	-0.0142[a]	-0.0654[a]	-0.0067[a]	0.0137[b]	-0.0158[c]
	(0.0012)	(0.0043)	(0.0041)	(0.0097)	(0.0014)	(0.0057)	(0.0092)
Profitability	-0.1415[a]	-0.0815[a]	-0.3101[a]	-0.1343[a]	0.0302[a]	-0.1296[a]	0.1045[a]
	(0.0056)	(0.0196)	(0.0248)	(0.0293)	(0.0059)	(0.0279)	(0.0251)
MV/BV	-0.0222[a]	-0.0353[a]	-0.0139[a]	-0.0006	0.0112[a]	-0.0270[a]	0.0071[a]
	(0.0006)	(0.0024)	(0.0025)	(0.0030)	(0.0007)	(0.0033)	(0.0027)
Tangibility	0.1715[a]	0.4749[a]	-0.1831[a]	-0.0387[a]	-0.0935[a]	-0.1434[a]	-0.0759
	(0.0102)	(0.0369)	(0.0323)	(0.0051)	(0.0125)	(0.0504)	(0.0556)
Earnings volatility	0.0035	-0.0098	-0.0012	0.1058[c]	0.0170	-0.0337	0.0023
	(0.0109)	(0.0411)	(0.0613)	(0.0583)	(0.0128)	(0.0412)	(0.0255)
Industry median leverage	-0.0104[a]	0.5667[a]	0.0047	-0.3015[a]	-0.1762[a]	-0.0411	-0.3104[b]
	(0.0029)	(0.0344)	(0.0046)	(0.1125)	(0.0172)	(0.0426)	(0.1305)
Dividend dummy	0.3878[a]	-0.0058[b]					
	0.0107	(0.0028)					
Year fixed effects	Yes	Yes					
N	140120	140093					
Adjusted R^2	0.1506	0.1849					

2003). Firms with higher $\overline{profit_i}$ have a more negative coefficient for profitability and are thus more sensitive to internal cash flows. In addition, they appear to be less sensitive to the changes in size, tangibility, earnings volatility and industry median leverage, all of which capture the costs and benefits considerations in the traditional tradeoff model. According to Frank and Goyal (2009), the tradeoff theory predicts positive coefficients for size and tangibility, yet the pecking order theory predicts negative coefficients for these two variables. The observation that firms with higher $\overline{profit_i}$ have less positive signs for size and tangibility may simply reflect the offsetting effects of firms' following a pecking order when raising external capital.

The interpretation for the interaction terms involving $\overline{scaled\ size_i}$ is less obvious. Consistent with the financial constraint interpretation, larger firms are more responsive to the changes in profitability and MV/BV. However, they also are less sensitive to the changes in size and tangibility. One possible explanation is that the negative signs for the interactions with size and tangibility reflect diminishing marginal effects of collateral values.

The particular set of variables we examine suggest two possible reasons why firms have heterogeneous slopes in the leverage models. First, firms with different levels of financial constraints can have different sensitivities toward the changes in the capital structure determinants. Second, capital structure theories are conditional theories, each applicable to a particular set of firms. Either reason can explain why firms may have different sensitivities toward changes in capital structure determinants.

Other possible explanations may also exist. Given that most of the competing capital structure theories are not mutually exclusive, it is a challenging task to rule out alternative explanations and provide a single definitive explanation for each of the interaction terms in Table 2.6. For the purpose of this paper, the most important implication of the results in Table 2.6 is that cross-sectional differences in slopes are related to economically meaningful factors and can possibly be explained with existing theories. Moreover, the results in Table 2.6 show that allowing the slopes to vary with these economically meaningful factors can lead to meaningful improvements in adjusted R^2. This is consistent with the view that slope heterogeneity can be a relevant explanation for the fixed effect puzzle documented by Lemmon, Roberts and Zender (2008).

6.2 Slope heterogeneity by industry

Firms in the same industry are likely to make similar capital structure choices because similar productive opportunities create incentives to adopt similar accounting practices and respond to the changes in the capital structure determinants in similar ways. If firm-specific slopes are related to industry factors, we expect to observe substantial differences in responsiveness to different capital structure determinants across industries. To examine the slope heterogeneity across industries, we estimate OLS and firm fixed effect leverage models separately for each industry. The explanatory variables include size, profitability, MV/BV, tangibility, earnings volatility and dividend dummy. Because the regressions are run for each industry, industry median leverage is not included in the model. The data are from the general sample. Industries with less than 200 observations are excluded. Firms with three digit SIC code 999 (nonclassifiable establishments) are also excluded.

The distribution of the estimated coefficients is presented in Table 2.7. For conciseness, only the results of the firm fixed effect models are presented. By controlling for unobserved heterogeneity, the fixed effect model produces more reliable estimates of the average effect within each industry. To be conservative, we focus on the distribution of coefficient estimates above the 20% percentile and below the 80% in our discussion. Even though this approach filters out a number of outliers, the differences within the 20%-80% range are still striking.[23] Take the coefficient for profitability for example. The coefficient is -0.1525 at the 80% percentile, -0.3487 at the 50% percentile and -0.6161 at the 20% percentile. Thus the capital structures of industries

[23] Qualitatively similar results are obtained using all coefficient estimates.

at the 20% percentile are almost four times more sensitive to profitability than those at the 80% percentile. The distribution in the Table 2.7 suggests that the assumption of homogeneous slopes is extremely unrealistic for the leverage models.

Using the same sample, we estimate a number of nested leverage models where the coefficients are interacted with industries dummies and/or firm characteristics. If the industry factors and firm characteristics are important sources of slope heterogeneity, these models will

Table 2.7. Slope Heterogeneity by industry

This table presents the distribution of the industry-specific slopes. The data are from the general sample described in Section 4. Industries with less than 200 observations are excluded. Firms with three digit SIC code 999 (nonclassifiable establishments) are also excluded. Separate firm fixed effect regressions are run for each three digit SIC industry. The dependent variable is market leverage. The explanatory variables include size, profitability, MV/BV, tangibility, earnings volatility and dividend dummy, as defined in Section 4.

	20%	30%	40%	50%	60%	70%	80%
Dividend dummy	-0.0549	-0.0426	-0.0297	-0.0181	-0.0069	0.0053	0.0176
Size	0.0298	0.0374	0.0471	0.0597	0.0684	0.0773	0.0923
MV/BV	-0.0529	-0.0459	-0.0394	-0.0334	-0.0277	-0.0198	-0.0139
Profitability	-0.6161	-0.4732	-0.3892	-0.3487	-0.2714	-0.2190	-0.1525
Earnings volatility	-0.4032	-0.2315	-0.1030	0.0329	0.1288	0.2279	0.3733
Tangibility	-0.0321	0.0280	0.0888	0.1511	0.1827	0.2215	0.2909

have significant improvements in model fit. The adjusted R^2 of the models, which penalize the inclusion of additional variables, are presented in Table 2.8.

Model I is a regression of market leverage on size, profitability, MV/BV, tangibility, earnings volatility, dividend dummy and year fixed effects. Notice there is no control for industry effects in Model I. Its adjusted R^2, 0.2307, is used as the benchmark for evaluating the explanatory powers of the industry factors and firm characteristics. Model II is similar to the model in Table 2.6. It includes the capital structure determinants in Model I and their interaction terms with the slope determinants $\overline{scaled\ size_i}$, $\overline{profit_i}$, $\overline{scaled\ MV/BV_i}$, $\overline{tangibility_i}$ and $\overline{earnings\ vol_i}$. After these interaction terms are included, the adjusted R^2 improves to 0.3302.

Models III, IV, and V evaluate the explanatory power of industry effects. Model III includes the capital structure determinants in Model I and three-digit SIC industry dummies. Model IV includes the capital structure determinants in Model I and their interaction terms with industry dummies, effectively allowing the slopes to vary by industry. It thus has industry-specific slopes, but not industry-specific intercepts. Model V includes the industry dummies, the capital structure determinants in Model I and their interaction terms with industry dummies. It thus has both industry-specific intercepts and industry-specific slopes. While the models appear to be complicated with the presence of the interaction terms, they are more parsimonious than the

Table 2.8. Industry, Firm characteristics and the Explanatory Powers of Models

This table presents the adjusted R^2 for different models. Model I is OLS regression of market leverage on size, profitability, MV/BV, tangibility, earnings volatility and dividend dummy, as defined in Section 4. Model II allows the slopes of the variables in Model I to vary with the slope determinants $\overline{Scaled\ size}$, $\overline{Profit}$, $\overline{Scaled\ MV/BV}$, $\overline{Tangibility}$ and $\overline{Earnings\ Vol}$. Model III includes Model I variables and industry dummies. Model IV allows slopes to vary by industry. Model V includes both industry-specific intercepts and industry-specific slopes. Model VI includes industry-specific intercepts and allows slopes to vary both by industry and by slope determinants.

	Adjusted R^2
Model I (base model)	0.2307
Model II (base model + interaction terms between capital structure determinants and slope determinants)	0.3302
Model III (base model + industry dummies)	0.3074
Model IV (Base model + interaction terms between capital structure determinants and industry dummies)	0.3505
Model V (Base model + industry dummies + interaction terms between capital structure determinants and industry dummies)	0.3608
Model VI (Base model + interaction terms between capital structure determinants and slope determinants + industry dummies + interaction terms between capital structure determinants and industry dummies)	0.4176

popular LSDV model. If the LSDV model is estimated using this sample, the model would include 9649 firm dummies.

The adjusted R^2 for Model III is 0.3074. The statistic is 0.3505 for Model IV and 0.3608 for Model V. Thus the adjusted $R^2$of Model V is 0.0103 higher than Model IV, yet 0.0534 higher than Model II. This indicates that the industry-specific slopes contain substantial information beyond the industry-specific intercepts. Yet, adding industry-specific intercepts adds remarkably little to the model fit once account is taken of the slope heterogeneity across industries. A comparison of model fit for the three models indicates that firms in the same industry share similarities in their capital structure decisions. However, such similarities are reflected not so much by a specific level of leverage that the industry is associated with as by the way the firms in the industry respond to the changes in capital structure determinants.

Model VI includes the industry dummies and allows the slopes to vary with both the industry dummies and the slope determinants. It has an adjusted R^2 of 0.4176, almost twice larger than the base model. The results in Table 2.8 show that meaningful improvements in model fit can be achieved if the slopes of the capital structure determinants are allowed to vary with industry and firm characteristics. This provides further evidence that the slope heterogeneity in the leverage models are related to industry factors and firm characteristics.

7. Conclusion

In this paper, we explore the issues related to the firm-specific heterogeneity in leverage models. The unobserved heterogeneity can be modeled either by heterogeneous intercepts or by heterogeneous slopes. The heterogeneous slopes assumption implies that different firms respond differently to the changes in capital structure determinants. The heterogeneous intercepts are often interpreted as implying that firms are associated with firm-specific leverage levels that remain stable over a long period. The appropriateness of the assumptions depends on the underlying data generating process. We show that the LSDV and fixed effect models can produce "pseudo fixed effects" when they are used to estimate data generating processes that are characterized with heterogeneous slopes. The "pseudo fixed effects" are the mechanical effects caused by the neglect of slope heterogeneity. Their presence should not be interpreted as evidence of time invariant leverage targets or evidence that the previous identified determinants are unimportant.

We apply various heterogeneous panel methods to the Survivor sample. Using the $\tilde{\Delta}$ test recently developed by Pesaran and Yamagata (2008), we formally test and reject the assumption of slope homogeneity. To make more reliable assessment about the importance of the previously identified determinants, we estimate the leverage equations using random coefficient/multilevel models. We find the previously identified determinants can explain more variation in leverage than what is suggested by the OLS or fixed effect models. Moreover, when heterogeneous slopes are specified for the capital structure determinants, adding heterogeneous intercepts to the model only marginally improves the model fit. To address the concern about over-fitting, we compare the out-of-sample predictive performances of the models. We find the random coefficient/multilevel models have substantially smaller MSE than the LSDV and fixed effect models. These results suggest that the firm-specific heterogeneity is reflected more by heterogeneous slopes than by heterogeneous intercepts.

Then we examine the slope heterogeneity in a more general sample. We find the slope heterogeneity in leverage models are related to industry factors and firm characteristics. This suggests that the cross-sectional differences in slopes are not merely a statistical artifact. They are driven by economically meaningful factors. Our evidence indicates that financial constraints can play a role in determining the slope heterogeneity across firms. In addition, we find that the cross-sectional differences in slopes can reflect the conditional applicability of capital structure theories, as suggested by Myers (2003).

Overall, the evidence in this paper leads to the following conclusions. First, it is more appropriate to view firms as having heterogeneous responses to the changes in capital structure determinants than to view them as being associated with firm-specific, time invariant levels of debt ratios. Second, a substantial proportion of the fixed effects in leverage models are “pseudo fixed effects”. They cannot be used as evidence for time invariant leverage targets. Third, the previously identified determinants can explain substantially more variation in leverage than what is suggested by the fixed effect model.

Appendix 2.1. Variable definitions

This appendix provides details about how the variables are constructed from Compustat data.
Total Debt = Short Term Debt (DLC) + Long Term Debt (DLTT)
Market Equity = Stock Price (PRCC_f) * Shares Outstanding (CSHO)
Market Leverage = Total Debt/(Total Debt + Market Equity)
Book Leverage = Total Debt/Total Assets (AT)
Firm Size = Log(Total Assets adjusted for inflation)
Profitability = Operating Income after Depreciation (OIADP)/Total Assets (AT)
MV/BV = (Market Equity + Total Debt + Preferred Stock Liquidating Value (PSTKL) – Deferred Tax and Investment Tax Credits (TXDITC))/Total Assets (AT)
Tangibility = Net PPE (PPENT)/Total Assets (AT)
Earnings Volatility = Rolling 10 Year Standard Deviations of Profitability (minimum three years of data are required for calculating the variable)

Appendix 2.2. $\tilde{\Delta}$ test

The $\tilde{\Delta}$ test can be used to test the hypothesis of slope homogeneity. The test statistic is

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{1}$$

where

$$\tilde{S} = \sum_{i=1}^{N} \left(\widehat{\beta}_i - \widehat{\beta}_{WFE}\right)' \frac{X_i' M_\tau X_i}{\widehat{\sigma}_i^2} \left(\widehat{\beta}_i - \widehat{\beta}_{WFE}\right) \tag{2}$$

$$\widehat{\sigma}_i^2 = \frac{\left(y_i - X_i \widehat{\beta}_{FE}\right)' M_\tau \left(y_i - X_i \widehat{\beta}_{FE}\right)}{T - 1} \tag{3}$$

$$\widehat{\beta}_{WFE} = \left(\sum_{i=1}^{N} \frac{X_i' M_\tau X_i}{\widehat{\sigma}_i^2}\right)^{-1} \sum_{i=1}^{N} \frac{X_i' M_\tau y_i}{\widehat{\sigma}_i^2} \tag{4}$$

In equations (1) – (4), k is the number of regressors and M_τ equals $I_T - \tau_T\left(\tau_T' \tau_T\right)^{-1} \tau_T'$. Intuitively, equations (3) and (4) construct a weighted FE pooled estimator of slope coefficients. $\tilde{S}$ in equation (2) measures the deviations of individual slopes from the weighted FE estimator. Equation (1) uses $\tilde{S}$ to calculate a standardized dispersion statistic. Pesaran and Yamagata (2008) show that for static models with non-normal error terms, the test statistic follows a standard normal distribution if $\sqrt{N}/T^2 \rightarrow 0$ as $(N, T) \rightarrow \infty$. With normally distributed errors, the distribution of test statistic is standard normal regardless of the expansion rates of N and T.

Appendix 2.3. Reduced form model of Equations (18) and (19)

$$
\begin{aligned}
L_{i,t} = {} & \beta_1 size_{i,t-1} + \beta_2 profit_{i,t-1} + \beta_3 MV/BV_{i,t-1} + \beta_4 tangibility_{i,t-1} + \beta_5 ind\ leverage_{i,t-1} \\
& + \beta_6 earnings\ vol_{i,t-1} + \beta_7 dividend_{i,t-1} + \eta_{1,1} size_{i,t-1} \times \overline{scaled\ size}_i + \eta_{2,1} size_{i,t-1} \\
& \times \overline{profit}_i + \eta_{3,1} size_{i,t-1} \times \overline{scaledMV/BV}_i + \eta_{4,1} size_{i,t-1} \times \overline{tangibility}_i \\
& + \eta_{5,1} size_{i,t-1} \times \overline{earnings\ vol}_i + \eta_{1,2} profit_{i,t-1} \times \overline{scaled\ size}_i + \eta_{2,2} profit_{i,t-1} \\
& \times \overline{profit}_i + \eta_{3,2} profit_{i,t-1} \times \overline{scaled\ MV/BV}_i + \eta_{4,2} profit_{i,t-1} \times \overline{tangibility}_i \\
& + \eta_{5,2} profit_{i,t-1} \times \overline{earnings\ vol}_i + \eta_{1,3} MV/BV_{i,t-1} \times \overline{scaled\ size}_i + \eta_{2,3} MV/BV_{i,t-1} \\
& \times \overline{profit}_i + \eta_{3,3} MV/BV_{i,t-1} \times \overline{scaledMV/BV}_i + \eta_{4,3} MV/BV_{i,t-1} \times \overline{tangibility}_i \\
& + \eta_{5,3} MV/BV_{i,t-1} \times \overline{earnings\ vol}_i + \eta_{1,4} tangibility_{i,t-1} \times \overline{scaled\ size}_i \\
& + \eta_{2,4} tangibility_{i,t-1} \times \overline{profit}_i + \eta_{3,4} tangibility_{i,t-1} \times \overline{scaledMV/BV}_i \\
& + \eta_{4,4} tangibility_{i,t-1} \times \overline{tangibility}_i + \eta_{5,4} tangibility_{i,t-1} \times \overline{earnings\ vol}_i \\
& + \eta_{1,5} ind\ leverage_{i,t-1} \times \overline{scaled\ size}_i + \eta_{2,5} ind\ leverage_{i,t-1} \times \overline{profit}_i \\
& + \eta_{3,5} ind\ leverage_{i,t-1} \times \overline{scaledMV/BV}_i + \eta_{4,5} ind\ leverage_{i,t-1} \times \overline{tangibility}_i \\
& + \eta_{5,5} ind\ leverage_{i,t-1} \times \overline{earnings\ vol}_i + \eta_{1,6} earnings\ vol_{i,t-1} \times \overline{scaled\ size}_i \\
& + \eta_{2,6} earnings\ vol_{i,t-1} \times \overline{profit}_i + \eta_{3,6} earnings\ vol_{i,t-1} \times \overline{scaledMV/BV}_i \\
& + \eta_{4,6} earnings\ vol_{i,t-1} \times \overline{tangibility}_i + \eta_{5,6} earnings\ vol_{i,t-1} \times \overline{earnings\ vol}_i \\
& + u_i
\end{aligned}
$$

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CHAPTER III

SIZE AND BOOK-TO-MARKET BASED RELATIVE PERFORMANCE EVALUATION IN EXECUTIVE COMPENSATION

1. Introduction

The relative performance evaluation of chief executive officers is a matter of much study and debate. According to principal-agency theory, firms can contract more efficiently with CEOs by evaluating their performance relative to a group of peer companies. However, the empirical literature provides limited support for the relative performance evaluation model. Except for the early study by Gibbons and Murphy (1990), previous research finds little evidence for the use of relative performance evaluation in deciding CEO compensation (e.g., Antle and Smith (1986), Barro and Barro (1990), Janakiraman, Lambert, and Larcker (1992), and Aggarwal and Samwick (1999)). These studies focus on whether CEOs are rewarded on the basis of relative industry performance[24]. Little attention is given to the relative performance evaluation against other reference groups, such as companies with similar size or market-to-book ratios. In this paper, I examine whether boards of directors evaluate CEOs' performances relative to their size and book-to-market peer groups.

There are two advantages of using size and book-to-market peer groups for testing the relative performance evaluation model. First, while there is substantial stock return co-movement among firms in the same industry, industry is not a widely accepted asset pricing factor as the size and book-to-market factors are. Fama and French (1994) model industry stock performances using their three factor model, which includes the size factor (SMB) and book-to-market factor (HML) as explanatory variables. To the extent that the size and book-to-market effects underlie

[24] Bizjak, Lemon and Naveen (2008) and Faulkender and Yang (2010) study the competitive benchmarking peers disclosed by companies. However, they focus on how these disclosed peers are used to extract rent or to determine competitive pay levels for retaining executives rather than on relative performance evaluation.

industry stock price movements, size and book-to-market peer groups may serve as better proxies for the common performance shocks. Second, strategic interactions may exist among firms in the same industry, offsetting the effects of relative performance evaluation. For example, Aggarwal and Samwick (1999) point out that the need to soften product market competition may cause boards to reward, rather than penalize, CEOs for the good performance of industry peers. Such product market competition is less a concern when the stock returns on size and book-to-market peer groups are used as proxies for testing the relative performance evaluation model.

I find that boards pay CEOs less (more) when their size and book-to-market peers perform well (poorly). This is consistent with the predictions of the relative performance evaluation model. I also find a negative relation between CEO cash compensation and the adjusted returns of the firms' size peer groups. I then examine whether my findings are driven by managerial entrenchment: entrenched managers may also seek to be evaluated against their size and book-to-market peers, but only when it is to their benefit to do so. In other words, they may seek to be evaluated only when their peer companies perform poorly. I find the negative relation between total compensation exists both in situations where the peer groups perform poorly and in situations where the peer groups perform well. My findings thus cannot be explained by managerial entrenchment. My main results are robust to the inclusion of various control variables and alternative proxies for peer group performances.

The rest of the paper proceeds as follows. Section 2 reviews the existing literature. Section 3 provides the data and descriptive statistics. Section 4 presents the main results of the paper. Section 5 reports the results of my robustness checks. Section 6 concludes.

2. Literature review

According to the principal agent model, boards can align CEOs' interests with shareholders' by linking CEO compensation to firm performance. In this context, boards reward

CEOs for unobserved effort by making inferences from firm performance. When some performance can also be attributed to factors beyond CEO control, such as industry wide shocks, firm performance is not sufficient to identify CEO effort. Risk averse CEOs will require higher compensation and/or exert suboptimal levels of effort if exogenous factors influence compensation. The relative performance evaluation model predicts that a well designed contract for risk averse CEOs filter common risks by benchmarking performance relative to appropriately chosen peer groups. Formally, suppose there are n CEOs and the i-th CEO's output is

$$y_i = a_i + \varepsilon_i + \theta \qquad (1)$$

where a_i is the i-th CEO's effort, ε_i the idiosyncratic noise and θ a common shock. Under the assumption that ε_i*'s* are independently and identically distributed, Gibbons and Murphy (1990) suggest that θ can be estimated as

$$\theta = \bar{y} - \bar{a} \qquad (2)$$

where $\bar{y}$ is the average output and $\bar{a}$ the average effort. Holmstrom (1982) shows that, under weak assumptions, the optimal compensation contract for the i-th CEO is a function of y_i and $\bar{y}$.

Consistent with the predictions of the relative performance evaluation model, Gibbons and Murphy (1999) find that the growth in CEO cash compensation is negatively and significantly related to industry performance, as measured by the stock returns of firms in the same sector[25]. Other studies are not successful in finding support for the relative performance evaluation model. For example, Jensen and Murphy (1990) find that relative performance evaluation does not appear to be an important source of managerial incentive. Antle and Smith (1986) decompose firm performance into industry and firm specific components and find that the industry component is positively related to the CEO compensation. This is inconsistent with the prediction that boards filter industry wide shocks. Barro and Barro (1990), Janakiraman, Lambert,

25 Gibbons and Murphy (1999) use 1-digit SIC code to identify sectors. When they extend their analysis to 2- and 3-digit SIC industries, they find no evidence that CEO compensation is negatively related to industry returns.

and Larcker (1992), and Aggarwal and Samwick (1999) all document a positive relation between CEO compensation and industry performance.

It has been argued that the paucity of evidence in support of the relative performance evaluation model could be partly attributed to the strategic interactions among firms. Aggarwal and Samwick (1999) articulate the view that CEOs will take actions to reduce industry returns if they are penalized for good industry performance. They show that the need to soften product market competition can generate an optimal compensation contract that rewards the CEO for both own and rival performances. Since previous studies on relative performance evaluation focus on industry peers, their results are potentially affected by the strategic interactions among firms in the same industry. In this paper, I examine whether boards, in deciding CEO compensation, filter the common shocks that are reflected in peer groups that are formed based on size and book-to-market ratios. My approach is less affected by product market competition because peer groups are formed by size and book-to-market ratio, rather than by industry.

My motivation for using size and book-to-market peer groups is based on the importance these factors have in explaining variation in cross-sectional returns. Fama and French (1992) find that size and book-to-market ratio are related to firms' stock performance. Their 1995 paper documents the size and book-to-market effects in earnings. Researchers have offered several economic interpretations for these two empirically identified factors. For example, Fama and French (1996) and Vassalou and Xing (2004) argue that size and book-to-market effects are related to financial distress. Several other studies relates the size and book-to-market effects to future investment opportunities and/or the riskiness of asset-in-place (Fama and French (1993), Petkova (2006), Gomes, Kogan and Zhang (2003), Carlson, Fisher and Giammarino (2004)).

To test the relative performance evaluation model, I follow Fama and French's (1993) argument that size and book-to-market effects proxy for sensitivity to common risk factors. The question of whether the differences in sensitivities between large and small firms and between low and high book-to-market firms are driven by the differences in default risk, growth opportunity or other factors, such as operating leverage, is less important for the purpose of my study. Under this theoretical framework, companies with similar size or book-to-market ratios have similar degrees of sensitivities to common risk factors. Under this assumption, equation (1) becomes

$$y_i = a_i + \varepsilon_i + b_j\theta \tag{3}$$

where b_j is the sensitivity of companies in size or book-to-market group j to common risk θ. When the output is as specified in equation (3), simply averaging across firms cannot isolate the impact of common shock θ, but produces estimate of $\overline{b_j\theta}$. By averaging within peer groups, $b_j\theta$ can be more precisely estimated as

$$b_j\theta = \overline{y_j} - \overline{a_j} \tag{4}$$

where $\overline{y_j}$ is the average output of companies in group j and $\overline{a_j}$ the expected effort of CEOs in group j. In other words, the board can obtain more precise estimate of the impact of the common risk by evaluating the CEO relative to his peers in the same size or book-to-market group.

Equations (3) and (4) assume that the stock prices of firms with different size and book-to-market ratios respond differently to a single aggregate shock. This is consistent with the theoretical models in Gomes, Kogan and Zhang (2003) and Carlson, Fisher and Giammarino (2004). Empirically, Petkova (2006) finds that the SMB and HML factors (i.e., the stock return spread between small and large firms and that between the low and high book-to-market firms) are correlated with innovations in various macroeconomic factors, such as aggregate dividend yield, term spread, default spread and one-month T-bill rate. This suggests that the stock price effects of the shocks to these macroeconomic factors differ systematically by size and book-to-market ratio, as equations (3) and (4) imply.

The discussion above suggests that the stock returns of firms with similar size and book-to-market ratios contain important information about common shocks. According to the relative performance evaluation model, boards can improve the efficiency of CEO compensation contracts by, explicitly or implicitly, evaluating performance relative to their size and book-to-market peers groups. If boards indeed filter common shocks related to size and book-to-market effects, there will be a negative relation between CEO compensation and the performance of their size and book-to-market peers. This leads to the main hypothesis of this paper, which is stated as follows:

H1: CEO compensation is negatively related to the performances of companies with similar size and/or book-to-market ratios.

To test this hypothesis, I build size and book-to-market peer groups for each company in my sample. I regress measures of executive compensation on own stock return and peer group returns. If the board filters common risk factors, CEO compensation will be negatively and significantly related to peer group returns.

The relative performance evaluation model predicts that boards filter common shocks both in situations where peer groups perform well and in situations where peer groups perform poorly. However, if entrenched CEOs can truly influence the setting of their pay, they will seek to be evaluated relative to peer groups only when it is to their benefit to do so. One possibility is that they will seek to be evaluated relative to their size and/or book-to-market peer groups when peer groups perform poorly, but not when peer groups perform well. This leads to the second hypothesis of this paper, which is stated as follows.

H2: CEO compensation is less negatively related to the performance of the firm's size and book-to-market peers when the peers perform well than when they perform poorly.

3. Data

The initial sample consists of all CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. This covers more than the whole universe of the S&P 1500 companies. I obtain stock returns from the

CRSP monthly stock return database. To be included in the sample, an observation should have twelve months of stock returns before a fiscal year end. I then match the sample to the accounting information from Compustat. I require that a sample observation has the lagged book equity information for calculating book-to-market ratio. Over the entire sample period, there are more than 3000 cases of CEO turnovers. At CEO turnover years, the lagged firm performances reflect the departing CEOs' performances rather than the succeeding CEOs' performances. I therefore delete observations for a CEO's first year of service for a company. The resulting sample consists of 21,794 CEO-firm-year observations. Depending on the availability of the control variables used, the sample is smaller when some of the regression models are estimated.

For each CEO-firm-year observation, I form size and book-to-market peer groups. The size peer groups are constructed from the companies listed in the Execucomp database for the same fiscal year. I calculate the size of a sample firm as its market value of equity at the beginning of the previous fiscal year. I then calculate the market values of other Execucomp companies as of the same calendar month. Based on their market values, I divide the companies into deciles using NYSE size breakpoints. The size peer group of a sample company consists of all Execucomp companies in the same decile. I construct size and book-to-market peer groups using firms that are in the Execucomp database because these are the most visible firms on the market, to which boards are most likely to pay attention. In my robustness check, I use peer groups that are constructed using all firms that are in the Compustat CRSP linked database. I calculate median buy-and-hold returns (BHARs) of peer groups for the twelve months after group formation and use it as the size benchmark for evaluating the performance of the sample company. This procedure ensures that the stock returns of the sample firms and size benchmark returns are calculated over the same 12-month period, regardless of the sample firms' choices of fiscal year end month.

The same procedure is used to construct the book-to-market peer groups for the sample companies. Based on the book-to-market ratios that are known at the beginning of the fiscal year, I assign sample firms into book-to-market deciles using NYSE breakpoints. The book-to-market peer group for each sample company consists of all other Execucomp companies that are in the same book-to-market decile for the same calendar month. I assume that the book values for calculating the book-to-market ratios become known to the public four months after the fiscal year end.

The performance of the size and book-to-market peer groups can be measured using median return, value weighted return or equal weighted return. Value weighted return is not the most appropriate measure for the purpose of this paper. In this paper, peer group performances are used as proxies for the impact of common shocks. Unless returns of large stocks are better proxies for the impact of common shocks, there is no reason to put more weight on them. In fact, if the main hypothesis regarding size based relative performance evaluation holds, the value weighted market return is most probably an inaccurate proxy of common shocks. The advantage of median returns is that they are less affected by extreme values than equal weight returns are. Therefore, I use median returns as the measures of peer group performances in my base models. I nevertheless use equal weighted returns of size and book-to-market peer groups in my robustness check. To avoid mechanical correlations, I exclude own stock returns in calculating the benchmark returns. If a peer company is delisted after peer group formation, I invest delisting proceeds to value weighted CRSP index so that it remains in the peer group. This mitigates potential survivorship bias. I adjust the returns of the size and book-to-market peer groups by subtracting the market return, which is calculated as the median return of all Execucomp companies. I refer to the adjusted returns of the size groups are referred to as the size return and those of the book-to-market peer groups as the BM returns.

Table 3.1 presents the descriptive statistics. Total compensation is the TDC1 variable in the Execucomp database, which is the sum of salary, bonus, restricted stock grants, long term incentive plan payouts, value of stock option grants and all other compensation. Cash compensation is the sum of salary and bonus. Following previous research, I adjust the compensation items for inflation based on the CPI data from the Bureau of Labor Statistics, using December 1994 as the base period. The median total

Table 3.1. Descriptive Statistics

The sample consists of CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. Observations with missing book or market value of equity and those involving CEO turnovers are excluded. Total compensation is the the sum of salary, bonus, restricted stock grants, long term incentive plan payouts, value of stock option grants and all other compensation. Cash compensation is the sum of salary and bonus. Stock return is a sample firm's buy-and-hold return over the fiscal year. Market return is the measured as the median return of all Execucomp companies during the year. Size (BM) return is defined as the median return of a sample firm's size (book-to-market) peer groups minus market return. R&D is research and development expenditure scaled by sales. PP&E is net plant, property and equipment scaled by assets. Volatility is the standard deviation of a sample firm's stock return over the 12 month buy-and-hold period. Total compensation, cash compensation and sales are deflated using 1994 as the base period. To mitigate the influence of outliers, R&D is winsorized at 99%, and volatility and book-to-market ratio at 1% and 99%.

	N	Median	Mean	Std
Total compensation	21794	1,848	3,724	8,853
Log(total compensation)	21794	7.5224	7.5566	1.1502
Cash compensation	21794	721	1,069	1,571
Log(cash compensation)	21794	6.5814	6.5962	0.9600
Stock return	21794	0.0776	0.1287	0.4911
Market return	21794	0.0738	0.0676	0.1742
Size return	21794	0.0029	0.0016	0.0742
BM return	21794	-0.0007	-0.0019	0.0627
Assets	21794	1,224	9,519	47,608
Market value	21794	1,097	5,252	17,294
Sales	21790	930	3,772	11,255
R&D	21777	0.0000	0.0402	0.1046
PP&E	21236	0.2152	0.2814	0.2378
Volatility	21794	0.0949	0.1112	0.0638
BM	21794	0.4772	0.5713	0.4293

compensation for CEOs in the sample is $1,848 thousand and the mean is $3,724 thousand. The median cash compensation, in 1994 dollars, is $721 thousand and the mean is $1,069 thousand. Because both variables are substantially skewed, I use their logarithmic transformations in my regression analysis. From 1994 to 2008, the median stock return for sample firms is about 7.76% per year. By design, this is similar to the median market return, which is defined as the median return for all Execucomp firms for a particular year. The size and BM returns are defined as the median return of a sample firm's size and book-to-market peer groups minus the market return.

Consequently, their means and median are all close to zero. In Table I, I also provide the descriptive statistics for several other variables that are used in my regressions. R&D is defined as research and development expenditure scaled by sales, PP&E defined as net plant, property and equipment scaled by assets and volatility as the standard deviation of a sample firm's stock return over the 12 month buy-and-hold period. To mitigate the influence of outliers, I winsorize R&D at 99%, and volatility and book-to-market ratio at 1% and 99%.

Table 3.2.: Correlation between market return, size return and BM return

The sample consists of CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. Observations with missing book or market value of equity and those involving CEO turnovers are excluded. Market return is the measured as the median return of all Execucomp companies during the year. Size (BM) return is defined as the median return of a sample firm's size (book-to-market) peer groups minus market return.

	Size return	BM return	Market return
Size return	1	0.08228	0.06987
BM return		1	0.0047
Market return			1

Table 3.2 presents the Pearson correlation between the median stock returns of the peer groups. The correlation is 0.0699 between market return and size return, 0.0047 between market return and BM return and 0.0823 between size return and BM return.

4. Results

In this section, I examine whether boards evaluate firm performance relative to their size and book-to-market peers in deciding CEO compensation. Following Gibbons and Murphy (1990), I regress measures of executive compensation on firms' own stock returns and the stock performances of their size and BM based peers. If boards filter common shocks related to size and book-to-market effects, the compensation measures will be negatively related to the peer group stock performances.

Panel A of Table 3.3 presents the results from regressing the natural log of CEO total compensation on the stock return variables. The t statistics in the parentheses are calculated using standard errors clustered by firm. Year and industry fixed effects are included. The OLS models in the first three columns estimate the relation between total compensation and peer group returns, after controlling for own stock return and market return. In all three models, CEO compensation is positively related to firm's own performance and negatively related to the market performance. More importantly, the coefficients for size and BM returns are all significantly negative, indicating that the CEOs are rewarded (or penalized) less when their size and book-to-market peer groups perform better (worse). This is consistent with the prediction of the relative performance evaluation model. In Model (3), the returns of the overall market, the size peer group and the book-to-market peer groups correspond to the three risk factors in the Fama French model. The coefficients for market return, size return and BM returns are, respectively, -0.2831, -0.9130 and -0.3154, The performance of size and book-to-market peer groups appear to have more impact on CEO total compensation than the overall market. In Models (4), (5) and (6), I estimate the relation between total compensation and peer group performance using the fixed effect model. The inclusion of fixed effects controls for all factors about the firm, such as average firm size and PP&E, that are constant over time. In all three models, the coefficients for market return, size return and BM return are significantly negatively related to total compensation. The magnitudes of the coefficients for size and BM returns are smaller than in Models (1), (2) and (3), but are still non-trivial compared with the coefficients for own stock return and market return. The results in Panel A are consistent with the view that boards make relative performance adjustments when deciding CEO's total compensation.

Panel B of Table 3.3 presents the results using the natural log of cash compensation as

Table 3.3.: Regression of executive compensation on size and BM returns

The sample consists of CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. Observations with missing book or market value of equity and those involving CEO turnovers are excluded. Total compensation is the the sum of salary, bonus, restricted stock grants, long term incentive plan payouts, value of stock option grants and all other compensation. Cash compensation is the sum of salary and bonus. Stock return is a sample firm's buy-and-hold return over the fiscal year. Market return is the measured as the median return of all Execucomp companies during the year. Size (BM) return is defined as the median return of a sample firm's size (book-to-market) peer groups minus market return. Columns (1), (2) and (3) present OLS estimates and columns (4), (5) and (6) present fixed effect estimates. The t values in the parentheses are calculated using standard errors clustered by firm. Year fixed and three-digit SIC industry dummies are included. a and b denote statistically significant at 1% and 5%.

Panel A: Log(total compensation) as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	6.8221[a]	6.8412[a]	6.7948[a]	-	-	-
	(13.98)	(14.40)	(13.72)			
Stock return	0.2161[a]	0.2073[a]	0.2266[a]	0.1419[a]	0.1389[a]	0.1479[a]
	(11.55)	(11.15)	(11.96)	(9.14)	(8.99)	(9.54)
Market return	-0.2216[c]	-0.3196[a]	-0.2661[b]	-0.6447[a]	-0.6696[a]	-0.6589[a]
	(-1.84)	(-2.71)	(-2.23)	(-10.35)	(-11.00)	(-10.78)
Size return	-0.9552[a]		-0.9130[a]	-0.3981[a]		-0.3807[a]
	(-8.54)		(-8.26)	(-5.11)		(-4.94)
BM return		-0.7868[a]	-0.7123[a]		-0.3696[a]	-0.3431[a]
		(-6.17)	(-5.72)		(-3.92)	(-3.68)
Firm fixed	No	No	No	Yes	Yes	Yes
R2	0.1469	0.1451	0.1483	0.0792	0.0786	0.0801

Panel B: Log(cash compensation) as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	5.8952[a]	5.9148[a]	5.8907[a]	-	-	-
	(25.73)	(24.89)	(25.58)			
Stock return	0.1895[a]	0.1812[a]	0.1912[a]	0.1665[a]	0.1586[a]	0.1650[a]
	(13.50)	(12.98)	(13.40)	(14.72)	(13.75)	(14.54)
Market return	-0.2758[b]	-0.3108[a]	-0.2831[a]	0.0234	0.0203	0.0273[a]
	(-3.15)	(-3.57)	(-3.23)	(0.50)	(0.43)	(0.58)
Size return	-0.4799[a]		-0.4731[a]	-0.2671[a]		-0.2716[a]
	(-4.48)		(-4.46)	(-3.33)		(-3.41)
BM return		-0.1545	-0.1159		0.0700	0.0889
		(-1.52)	(-1.17)		(0.96)	(1.23)
Firm fixed effects	No	No	No	Yes	Yes	Yes
R2	0.1595	0.1583	0.1596	0.0860	0.0850	0.0861

the dependent variable. The OLS results are presented in columns (1), (2) and (3) and the fixed effect results in columns (4), (5) and (6). The coefficients of market and size returns are negative and significant in all models, but the coefficients of BM returns are not. The results in Panel B provide support for the use of size based, but not for the use of book-to-market based, relative performance evaluation in deciding cash compensation. Taken together, the results in Panels A and B suggest that BM return is a relevant benchmark for deciding equity based compensation and size return is a relevant benchmark for deciding both the cash and equity components in CEO compensation.

In Table 3.4, I present results with controls for firm characteristics. The dependent variable for the models in Panel A is total compensation in logarithms. The OLS results are presented in Models (1), (2) and (3) and the fixed effect results in Models (4), (5) and (6). The t statistics are calculated using standard errors clustered by firm. Year and three digit SIC industry dummies are included to control for time and industry specific effects. The control variables are similar to those used by Aggarwal and Samwick (1999). The coefficients of the control variables have signs and significance levels that are consistent with previous research. Companies of larger size, measured by the logarithm of lagged sales, provide higher compensation to their CEOs. R&D and book-to-market ratio, as proxies for monitoring costs and growth options, are positively related to CEO compensation. There is a negative relation between PP&E and compensation, consistent with the notion that companies with higher asset tangibility require less monitoring. For the OLS models, there is positive relation between volatility and total compensation. Most importantly, the key results regarding size and BM returns do not change after the inclusion of the control variables. Both of them remain negatively and significantly related to total compensation. Panel B of Table 3.4 presents estimation results for cash compensation. Consistent with previous research, there appear to be a negative relation between volatility and cash compensation. The coefficients for other control variables are similar to those in Panel A. More importantly, the results regarding size and BM returns are similar to those presented in Table 3.3. CEOs' cash compensation is negatively and significantly related to size return, but not to BM return.

Table 3.4.: Regression of executive compensation on size return, BM return and control variables

The sample consists of CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. Observations with missing book or market value of equity and those involving CEO turnovers are excluded. Total compensation is the the sum of salary, bonus, restricted stock grants, long term incentive plan payouts, value of stock option grants and all other compensation. Cash compensation is the sum of salary and bonus. Stock return is a sample firm's buy-and-hold return over the fiscal year. Market return is the measured as the median return of all Execucomp companies during the year. Size (BM) return is defined as the median return of a sample firm's size (book-to-market) peer groups minus market return. R&D is defined as research and development expenditure scaled by sales, PP&E defined as net plant, property and equipment scaled by assets and volatility as the standard deviation of a sample firm's stock return over the 12 month buy-and-hold period. To mitigate the influence of outliers, I winsorize R&D at 99%, and volatility and book-to-market ratio at 1% and 99%.Columns (1), (2) and (3) present OLS estimates and columns (4), (5) and (6) present fixed effect estimates. The t values in the parentheses are calculated using standard errors clustered by firm. Year fixed and three-digit SIC industry dummies are included. a and b denote statistically significant at 1% and 5%.

Panel A: Log(total compensation) as dependent variable

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Intercept	3.5922	a	3.6159	a	3.5842	a	-		-		-	
	(25.87)		(27.03)		(25.38)							
Stock return	0.1535	a	0.1472	a	0.1594	a	0.1012	a	0.0994	a	0.1071	a
	(8.39)		(8.12)		(8.76)		(6.00)		(5.89)		(6.36)	
Market return	-0.3194	a	-0.3743	a	-0.3402	a	-0.4203	a	-0.4443	a	-0.4350	a
	(-2.88)		(-3.42)		(-3.10)		(-6.90)		(-7.46)		(-7.29)	
Size return	-0.5256	a			-0.5073	a	-0.3038	a			-0.2876	a
	(-5.98)				(-5.86)		(-4.01)				(-3.84)	
BM return			-0.3562	a	-0.3154	a			-0.3247	a	-0.3037	a
			(-3.27)		(-2.94)				(-3.55)		(-3.35)	
Log(sales)	0.4724	a	0.4725	a	0.4720	a	0.3958	a	0.3953	a	0.3954	a
	(44.61)		(44.57)		(44.56)		(18.26)		(18.31)		(18.27)	
R&D	1.7584	a	1.7479	a	1.7521	a	0.3696	c	0.3426	c	0.3583	c
	(11.45)		(11.38)		(11.41)		(1.77)		(1.66)		(1.72)	
PP&E	-0.3365	a	-0.3424	a	-0.3369	a	-0.9255	a	-0.9426	a	-0.9278	a
	(-3.87)		(-3.94)		(-3.88)		(-7.95)		(-8.08)		(-7.98)	
Volatility	0.4839	b	0.4213	b	0.4613	b	0.1311		0.0840		0.1055	
	(2.44)		(2.13)		(2.34)		(0.80)		(0.52)		(0.65)	
BM	-0.2594	a	-0.2598	a	-0.2545	a	-0.2528	a	-0.2536	a	-0.2501	a
	(-9.00)		(-9.05)		(-8.93)		(-9.84)		(-9.85)		(-9.75)	

Table 3.4. (cont'd)

Firm fixed effects	No	No	No	Yes	Yes	Yes
R^2	0.4444	0.4437	0.4447	0.1444	0.1443	0.1451

Panel B: Log(cash compensation) as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	4.0558 [a]	4.0678 [a]	4.0563 [a]	-	-	-
	(20.76)	(19.74)	(20.74)			
Stock return	0.1806 [a]	0.1758 [a]	0.1802 [a]	0.1612 [a]	0.1542 [a]	0.1599 [a]
	(13.08)	(12.78)	(13.04)	(14.02)	(13.06)	(13.87)
Market return	-0.4085 [a]	-0.4195 [a]	-0.4072 [a]	0.1034 [b]	0.1000 [b]	0.1068 [b]
	(-4.95)	(-5.13)	(-4.94)	(2.10)	(2.05)	(2.18)
Size return	-0.1821 [c]		-0.1832 [b]	-0.2055 [a]		-0.2092 [a]
	(-1.93)		(-1.96)	(-2.58)		(-2.65)
BM return		0.0051	0.0198		0.0540	0.0693
		(0.06)	(0.22)		(0.74)	(0.97)
Log(sales)	0.2922 [a]	0.2924 [a]	0.2922 [a]	0.2325 [a]	0.2325 [a]	0.2326 [a]
	(27.96)	(27.96)	(28.00)	(9.96)	(9.98)	(9.96)
R&D	0.6075 [a]	0.6064 [a]	0.6079 [a]	-0.1834	-0.1922	-0.1808
	(4.62)	(4.62)	(4.62)	(-1.33)	(-1.40)	(-1.31)
PP&E	-0.1346 [c]	-0.1365 [c]	-0.1345 [c]	-0.4103 [a]	-0.4205 [a]	-0.4098 [a]
	(-1.69)	(-1.71)	(-1.68)	(-4.37)	(-4.47)	(-4.36)
Volatility	-1.0418 [b]	-1.0549 [a]	-1.0404 [a]	-0.7628 [a]	-0.7725 [a]	-0.7569 [a]
	(-6.13)	(-6.26)	(-6.15)	(-5.27)	(-5.36)	(-5.24)
BM	-0.0535 [b]	-0.0558 [b]	-0.0539 [b]	-0.0850 [a]	-0.0882 [a]	-0.0857 [a]
	(-2.04)	(-2.13)	(-2.07)	(-3.54)	(-3.65)	(-3.56)
Firm fixed effects	No	No	No	Yes	Yes	Yes
R^2	0.3404	0.3402	0.3404	0.1222	0.1216	0.1223

The results in Tables 3.3 and 3.4 are consistent with the relative performance evaluation model. However, they can also be consistent with managerial entrenchment hypothesis if the negative relation between compensation and peer group performance exists only in situations where relative performance evaluation is more favorable to CEOs. If entrenched managers can

Table 3.5. Regression of total compensation on size return, BM return and peer performance dummies

The sample consists of CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. Observations with missing book or market value of equity and those involving CEO turnovers are excluded. Total compensation is the the sum of salary, bonus, restricted stock grants, long term incentive plan payouts, value of stock option grants and all other compensation. Stock return is a sample firm's buy-and-hold return over the fiscal year. Market return is the measured as the median return of all Execucomp companies during the year. Size (BM) return is defined as the median return of a sample firm's size (book-to-market) peer groups minus market return. Sizedown (BMdown) is a dummy variable that takes the value of 1 when size (BM) peer groups have negative stock returns. R&D is research and development expenditure scaled by sales. PP&E is net plant, property and equipment scaled by assets. Volatility is the standard deviation of a sample firm's stock return over the 12 month buy-and-hold period. R&D is winsorized at 99%, and volatility and book-to-market ratio at 1% and 99%. The t statistics in the parentheses are calculated using standard errors clustered by firm. Year fixed and three-digit SIC industry dummies are included. a and b denote statistically significant at 1% and 5%.

	Model 1		Model 2	
Intercept	3.5983	a	-	
	(25.58)			
Stock return	0.1609	a	0.1084	a
	(8.82)		(6.41)	
Market return	-0.3482	a	-0.4388	a
	(-3.14)		(-7.26)	
Size return	-0.6156	a	-0.3710	a
	(-5.86)		(-4.08)	
Size return × Sizedown	0.4053	c	0.2802	c
	(1.75)		(1.68)	
BM return	-0.3183	b	-0.2395	b
	(-2.39)		(-2.20)	
BM return × Bmdown	-0.0172		-0.1732	
	(-0.06)		(-0.77)	
Log(sales)	0.4716	a	0.3943	a
	(44.37)		(18.14)	
R&D	1.7534	a	0.3599	c
	(11.42)		(1.73)	
PP&E	-0.3366	a	-0.9249	a
	(-3.88)		(-7.95)	
Volatility	0.4750	b	0.1070	c
	(2.41)		(0.67)	
BM	-0.2520	a	-0.2487	a
	(-8.88)		(-9.71)	
Firm fixed effects	No		Yes	
R^2	0.4448		0.1453	

truly influence boards' decisions, they will seek to be evaluated relative to their peers only when it is favorable to them. If so, the negative relation between CEO compensation and the peer group performances will exist only when peer companies are performing poorly, but not when peer companies are performing well. Such asymmetric effects are more consistent with the managerial entrenchment hypothesis than with the relative performance evaluation model. I test against the managerial entrenchment hypothesis using the regression models in Table 3.5. The OLS model in column (1) corresponds to Model (3) in Panel A of Table 3.4 and the fixed effect model in column (2) to Model (6) in Panel A of Table 3.4. Both models in include the interaction term between size return and sizedown and that between BM return and BMdown). Sizedown (BMdown) is a dummy variable that takes the value of 1 when size (BM) peer groups have negative stock returns and 0 otherwise. It is beneficial to the CEO to evaluate them relative to their size and BM peer groups when these peer groups generate negative stock performance. If the managerial entrenchment hypothesis holds, CEOs will be rewarded more for the poor performances of their size and BM peers than they are punished for the good performances of their peers. In other words, the interaction terms will be significantly negatively related to CEO compensation. Inconsistent with the managerial entrenchment hypothesis, the coefficient for Size return × Sizedown is positive. Although the coefficient for BM return × BMdown is negative, it is not significant at conventional significance levels. Overall, the results in Table 3.5 show no evidence that CEOs are rewarded more for the bad performances of their size and BM peers than they are punished for the good performances of these firms. This is more consistent with the relative performance evaluation model than with the managerial entrenchment hypothesis.

5. Robustness check

First, I check whether the results regarding size and book-to-market based relative performance evaluation are robust to the use of alternative measures of peer group performance.

In Section 4, I use the median returns of all Execucomp firms that are in the same size or book-to-market deciles as measures of peer group performances. Table 3.6 presents the results of OLS regression of CEOs' total compensation on alternative measures of peer group stock performances. The size and BM returns in Table 3.6 are the equal weighted returns of all CRSP firms, rather than just Execucomp firm, in the same size or book-to-market decile as the sample firm minus equal weighted market return. The size and book-to-market decile memberships are based on firms' market value of equity and book-to-market ratio that are known at the beginning of the fiscal year. In Models (1), (2) and (3), I examine the relation between CEOs' total compensation and the equal weighted returns of firms' size and book-to-market peer groups. In all three models, the coefficients for size and BM returns are negative and significant at 1% significance levels. Model (4) includes the equal weighted returns of firms' three-digit SIC industries minus equal weighted market return as a control variable. Consistent with the findings by Barro and Barro (1990), Janakiraman, Lambert, and Larcker (1992), and Aggarwal and Samwick (1999), the coefficient for industry return is positive and significant at 1% significance level. According to Aggarwal and Samwick (1999), the positive relation between CEOs' total compensation and industry return is driven by the need to soften product market competition. More importantly, after controlling for industry returns, the coefficients for size and BM returns remain consistent with the prediction of the relative performance evaluation model. Both of them are still significantly negatively related to CEOs' total compensation.

Next, I examine whether my main results are robust to the inclusion of various corporate governance variables. Previous research shows that firms' corporate governance practices affect executive compensation. The models in Table 3.7 include various corporate governance variables, such as log(board size), insider directors as a percentage of board and corporate governance index. Board size and insider percentage are calculated using data from the Risk Metrics Directors such as log(board size), insider directors as a percentage of board and corporate governance index. Board size and insider percentage are calculated using data from the Risk Metrics Directors database. Corporate governance index is from the Risk Metric Corporate Governance database.

The data requirement for the governance

Table 3.6.: Regression of total compensation on equal weighted returns

The sample consists of CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. Observations with missing book or market value of equity and those involving CEO turnovers are excluded. Total compensation is the sum of salary, bonus, restricted stock grants, long term incentive plan payouts, value of stock option grants and all other compensation. Stock return is a sample firm's buy-and-hold return over the fiscal year. Market return is the equal weighted CRSP return. Size (BM) return is defined equal weighted return of a sample firm's size (book-to-market) peer groups minus market return. Industry return is the equal weighted return of firms in the same 3-digit SIC industry minus equal weighted market return. R&D is research and development expenditure scaled by sales. PP&E is net plant, property and equipment scaled by assets. Volatility is the standard deviation of a sample firm's stock return over the 12 month buy-and-hold period. R&D is winsorized at 99%, and volatility and book-to-market ratio at 1% and 99%. The t values in the parentheses are calculated using standard errors clustered by firm. Year fixed and three-digit SIC industry dummies are included. a and b denote statistically significant at 1% and 5%.

	Model 1		Model 2		Model 3		Model 4	
Intercept	4.7486	a	5.1013	a	4.1511	a	3.9404	a
	(4.76)		(4.93)		(39.89)		(19.67)	
Stock return	0.1696	a	0.1724	a	0.1605	a	0.1642	a
	(6.86)		(6.98)		(6.41)		(5.69)	
Market return	-0.3946	a	-0.4049	a	-0.3049	a	-0.4119	a
	(-3.30)		(-3.39)		(-2.70)		(-3.26)	
Size return	-0.4966	a			-0.5512	a	-0.5729	a
	(-4.75)				(-5.33)		(-5.03)	
BM return	-0.2544	b	-0.2541	b	-0.3039	b	-0.2718	b
	(-2.04)		(-2.04)		(-2.42)		(-1.97)	
Board size	0.1025						0.0740	
	(1.56)						(1.03)	
%Insider			-0.5727	a			-0.4322	a
			(-4.12)				(-2.82)	
Gindex					0.0189	a	0.0113	b
					(3.55)		(1.99)	
Log(sales)	0.4656	a	0.4647	a	0.4718	a	0.4628	a
	(33.89)		(39.20)		(38.34)		(31.15)	
R&D	1.5616	a	1.5304	a	1.7285	a	1.6483	a
	(8.51)		(8.43)		(10.40)		(8.62)	
PP&E	-0.3784	a	-0.3692	a	-0.3699	a	-0.3803	a
	(-3.72)		(-3.67)		(-3.82)		(-3.55)	
Volatility	0.8142	a	0.7765	a	0.2710		0.6258	b
	(3.29)		(3.17)		(1.16)		(2.37)	
BM	-0.3400	a	-0.3427	a	-0.2947	a	-0.3287	a
	(-9.70)		(-9.75)		(-8.67)		(-8.75)	
R^2	0.4564		0.4585		0.4560		0.4705	

Table 3.7.: Regression of total compensation on size and BM returns with additional control variables

The sample consists of CEO-firm-year observations with nonmissing total compensation information during the period 1994 – 2008 from the Execucomp database. Observations with missing book or market value of equity and those involving CEO turnovers are excluded. Total compensation is the the sum of salary, bonus, restricted stock grants, long term incentive plan payouts, value of stock option grants and all other compensation. Stock return is a sample firm's buy-and-hold return over the fiscal year. Market return is the equal weighted CRSP return. Size (BM) return is defined equal weighted return of a sample firm's size (book-to-market) peer groups minus market return. Industry return is the equal weighted return of firms in the same 3-digit SIC industry minus equal weighted market return. R&D is research and development expenditure scaled by sales. PP&E is net plant, property and equipment scaled by assets. Volatility is the standard deviation of a sample firm's stock return over the 12 month buy-and-hold period. R&D is winsorized at 99%, and volatility and book-to-market ratio at 1% and 99%. The t values in the parentheses are calculated using standard errors clustered by firm. Year fixed and three-digit SIC industry dummies are included. a and b denote statistically significant at 1% and 5%.

	Model 1		Model 2		Model 3		Model 4	
Intercept	3.6504	a	4.6515	a	4.5861	a	4.5882	a
	(28.31)		(53.47)		(52.21)		(52.24)	
Stock return	0.1449	a	0.1370	a	0.1427	a	0.1279	a
	(7.84)		(7.28)		(7.59)		(6.40)	
Market return	-0.2763	a	-0.1607	a	-0.3368	a	-0.3199	a
	(-3.73)		(-2.46)		(-4.50)		(-4.27)	
Size return	-0.3469	a			-0.3469	a	-0.3186	a
	(-5.20)				(-5.20)		(-4.48)	
BM return			-0.2495	a	-0.1674	a	-0.1964	a
			(-4.14)		(-2.63)		(-3.06)	
Industry return							0.0692	a
							(2.67)	
Log(sales)	0.4727	a	0.4488	a	0.4486	a	0.4485	a
	(44.63)		(45.47)		(45.46)		(45.45)	
R&D	1.7507	a	1.7781	a	1.7819	a	1.7720	a
	(11.40)		(15.22)		(15.28)		(15.25)	
PP&E	-0.3404	a	-0.3188	a	-0.3174	a	-0.3178	a
	(-3.92)		(-5.09)		(-5.07)		(-5.06)	
Volatility	0.5114	a	0.5698	a	0.6081	a	0.6036	a
	(2.57)		(2.81)		(3.01)		(2.99)	
BM	-0.2624	a	-0.3193	a	-0.3207	a	-0.3178	a
	(-9.07)		(-11.28)		(-11.34)		(-11.17)	
R^2	0.4438		0.3761		0.3767		0.3767	

variables reduces the sample size substantially. For example, Model (4), in which all three governance variables are present, is estimated using 11,419 observations. In all four models, both size return and BM return are negatively and significantly related to total compensation.

Therefore, controlling for firms' corporate governance practices, the results are still consistent with the relative performance evaluation model.

In unreported analysis, I also examine whether the main results are affected by outliers. For a small portion of the observations, CEOs receive total compensation of $1 per year. A recent study by Guthrie, Sokolowsky and Wan (2010) shows that these observations may have nontrivial effects on estimation results. I thus re-estimate the models in Table 3.3 and 4 after excluding these extreme observations. The estimation results remain similar to those reported in Tables 3.3 and 3.4.

6. Conclusion

In this paper, I investigate whether boards make adjustments for the performances of size and book-to-market peer groups in deciding CEOs' compensation. My empirical results provide strong evidence in support of the use of size and book-to-market based relative performance evaluation in deciding total compensation. In addition, I find that boards adjust CEOs' cash compensation based on the performances of their size peer groups. The negative relations between CEOs' compensation and the performances of size and BM peer groups exist both in situations where the size and BM peer groups perform well and in situations where the peer groups perform poorly. My findings are thus more consistent with the relative performance evaluation model than with the managerial entrenchment hypothesis.

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