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Investigations into the Underpricing of Seasoned Equity Offerings and the Cost of Equity

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INVESTIGATIONS INTO THE UNDERPRICING OF SEASONED EQUITY OFFERINGS AND THE COST OF EQUITY

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Dedication

To my wife Hong Kim Duong and my sons Minh Duc Ngo and Hai Anh Ngo for their endless love, support and encouragement during my doctoral program.

To my parents, sisters, and brother for their love, encouragement, and unconditional support with my studies.

INVESTIGATIONS INTO THE UNDERPRICING OF SEASONED EQUITY OFFERINGS AND THE COST OF EQUITY

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Abstract

This dissertation consists of three separate but related essays investigating new determinants of the underpricing of seasoned equity offering (SEOs). It also examines new mechanisms and channels that affect the pricing of SEOs. The first essay examines the impacts of earnings smoothing on SEO underpricing. It aims to investigate whether earnings smoothing can add value to firms by reducing the degree of SEO underpricing. The findings show that smoothing earnings performance resulting from discretionary accruals is negatively related to SEO underpricing and improve earnings informativeness. This essay contributes specifically to the current literature on earnings smoothing by demonstrating that high quality firms that expect larger quantity of cash flow in the near future are more likely to actively smooth earnings via discretionary accruals before SEOs to reduce underpricing. The second essay explores the role of lines of credit in pricing seasoned equity offerings via market timing activities. This essay provides evidence that lines of credit, while not perfect substitutes for cash holdings, give firms the option to delay equity offerings until market conditions become more favorable, thereby creating value for current shareholders. Interestingly, these effects are not observed when firms are financially constrained. The third essay investigates the impact of covenant violations on SEO underpricing. It also directly quantifies the changes in implied cost of equity surrounding covenant violations. The results show that seasoned equity offerings are more underpriced after covenant violations. The findings show that firms that violate a covenant, on average, experience an 8.4 % increase in the implied cost of equity. This suggests that creditors may force violating firms to issue equity to lower leverage, thereby resulting in a higher degree of SEO underpricing through the SEO episodes.

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Chapter 1

Introduction

This dissertation consists of three separate, but related essays that investigate the roles of earnings smoothing (essay 1), lines of credit (essay 2) and covenant violations (essay 3) on the underpricing of seasoned equity offerings and the cost of equity capital.

There is a vast literature on the determinants of SEO underpricing. Both the theoretical and empirical papers published thus far explain SEO underpricing based on uncertainty or information asymmetry between issuers and outside investors, price pressure effects, pre-offer price move and trading manipulation, transaction cost saving, and underwriter price practice (e.g., Corwin et al., 2003). Prior studies based on uncertain or asymmetric information have documented that the level of SEO underpricing is correlated with the level of information asymmetry between issuers and investors. In a theoretical paper, Rock (1986) showed that underpricing is necessary to ensure uninformed investors' participation in the new offerings. Without such compensation, uninformed investors would be less likely to purchase new shares, because, in most cases, issuers are believed to issue only overvalued stock, as shown in the perking order model of Mayer and Majluf (1984). Beatty and Ritter (1986) found support for the positive relation between underpricing and ex ante uncertainty because of the winner's curse problem. Most empirical studies on SEO underpricing support the idea that underpricing is used as a mechanism to signal firm quality to outside investors under information asymmetry (Allen & Faulhaber, 1989; Baron, 1982; Benveniste & Spindt, 1989; Chemmanur, 1993). Along these lines, in the first two essays (chapter 2 and 3) I expand the current literature by examining two

new mechanisms that equity issuers can use to reduce their SEO underpricing via earnings smoothing and the use of lines of credit in fostering market timing activities.

More specifically, the first essay contributes to the current literature by investigating the effects of earnings smoothing on the underpricing of seasoned equity offerings. I find evidence that firms with a long period of earnings smoothing prior to SEOs are more likely high quality firms, which experience a lower degree of SEO underpricing. I also find that, based on the mean value for SEOs, such smoothing reduces underpricing by $0.33 per share and increases the value of the average offering by $1.65 million or 0.21 percent to the firm.

The second essay investigates the roles of lines of credit on SEO underpricing via market timing activity. I find that firms accessing lines of credit are more likely to actively time the market, because lines of credit, while not perfect substitutes for cash, give firms the option to delay equity offerings, thereby reducing the degree of SEO underpricing. Interestingly, these effects are not observed when firms are financially constrained.

The third essay (chapter 4) contributes to the current literature by quantifying the impacts of covenant violations on the implied cost of equity and on the pricing of post-covenant violation equity offerings. Using a unique dataset consisting of 1,045 first-time covenant violations from 1996-2011 of the US public firms and employing different models of implied cost of equity capital estimation, I find that firms that violate a covenant, on average, experience an 8.48% increase in the implied cost of equity capital. In addition, I also find a higher level of SEO underpricing for equity offerings conducted by violating firms during the period immediately following covenant violations. This suggests that creditors may require violating firms to issue equity to lower leverage, thereby resulting in a higher degree of SEO underpricing through the SEO episodes

Chapter 2

Earnings Smoothing and the Underpricing of Seasoned Equity Offerings[1]

2.1 Introduction

This chapter examines whether high quality firms with persistent earnings smoothing before a seasoned equity offering (SEO) can add value by reducing the offerings' underpricing. It provides new evidence on the positive relation between earnings smoothing and firm value through SEO episodes, and its support of the view that earnings smoothing via discretionary accruals improves the informativeness of future earnings. Based on the mean values for SEOs, such smoothing reduces underpricing by $0.33 per share and increases the value of the average offering by $1.65 million or 0.21 percent to the firm. This is a substantial increase in value that can be obtained from a smoothing earnings' strategy that, while relatively simple, is costly for underperforming firms. The loss in value from underperformance is consequently more than just the reduced stock price for outstanding shares. It includes a substantial opportunity loss associated with any new financing obtained from equity offerings. Managerial opportunism and information revealing hypothesis have been used in the literature to motivate earnings smoothing. Managerial opportunism motives argue that managers use accruals to exploit

1 This chapter was previously published as a research article (co-authored with Oscar Varela) with the same title in the Managerial Finance Journal, Volume 38, Issue 9, pp.833-859 (2012). The material in this chapter was co-authored by Anh Duc Ngo and Oscar Varela. Anh Duc Ngo had primary responsibility for generating the original research ideas, collecting and cleaning data, and conducting empirical tests. Anh Duc Ngo was the primary developer of the conclusions that are advanced here. Anh Duc Ngo also drafted the first version of this chapter. Oscar Varela contributed to this chapter by refining the original ideas into testable research questions and revising all versions of this chapter. See Appendix 2 for an email granting copyright permission from Emerald Group Publishing Limited.

information asymmetry, manipulating current earnings to achieve various benefits to themselves or their firms. Information revealing motives argue that managers smooth earnings to reveal information about the firms' future prospect. Both hypotheses have received support from a number of theoretical and empirical studies.

Studies supporting the hypotheses that managers are eager to stabilize their earnings in order to meet their bonus target or protect their job include the following. Bergstresser and Philippon (2006) document that managers whose compensation packages are sensitive to company share prices are more likely to lead their companies with higher level of earnings management. Fudenberg and Tirole (1995) construct a model to explain that managers use earnings smoothing as a vehicle to secure their job positions, and a series of studies, including Defond and Park (1997), have empirically supported this model.

Studies supporting the hypotheses that earnings smoothing can add value to firms by reducing information asymmetry include the following. Trueman and Titman (1988) provide evidence that high perceived earnings volatility increases the perceived risk of bankruptcy probability of the firms, hence its cost of external financing. Francis et al. (2006) examine the relation between cost of equity and seven attributes of earnings, including earnings smoothness, and find that earnings smoothness is negatively associated with cost of equity, even after accounting for cash flow volatility. Sankar and Subramanyam (2001) find that earnings smoothing can reveal managers' private information about future earnings, and conclude that there is information advantage to allowing reporting discretion when managers have private information beyond current earnings in a multi period framework. More recently, Tucker and Zarowin (2006) find that firms with earnings smoothing improve the use of current and past earnings in informing about future earnings forecasts leading to higher firm values. An

implication from their results is that earnings smoothing should result in value premiums, *ceteris paribus.*

In the present paper, using a sample of more than three thousand SEOs during the 21 year period 1989-2009, we find that smooth performance is negatively related to underpricing of seasoned equity offerings, such that smoothing via discretionary accruals adds value to firms by reducing the degree of SEO underpricing, while smoothing via cash flows does not.

Our findings are consistent with the results of recent studies on the effects of smooth performance on firm value. Graham et al. (2005) document that corporate managers perceived a positive market premium for lower earnings volatility, and Carter et al. (2006) find that the use of derivatives to stabilize earnings improves firm value. Roundtree et al. (2008) also find, using Tobin's Q as a proxy for firm value, that cash flow volatility has negative effect on firm value. However, in contrast to our findings, they also find that earnings smoothing via accruals does not add value.

Our findings that earnings smoothing reduces the degree of SEO underpricing lead us to also investigate whether the volatility of contemporaneous discretionary accruals convey information about future earnings, and through it, the underpricing of SEOs. The information revealing hypothesis suggests that earnings smoothing improves the informativeness of past and current earnings about future earnings. We consequently investigate the implications of this relationship for SEO underpricing and post-SEO performance for both groups of firms, namely high and low quality groups, consisting of firms with high and low levels of earnings smoothing, respectively.

Using a modified version of Jones (1991) model to estimate discretionary accruals, we find that the volatility of discretionary accruals is negatively associated with SEO underpricing,

whereas volatility of cash flow (over a five year period prior to the offer date) is not related to underpricing . These results are somewhat consistent with the findings of Subramanyam (1996), which show that discretionary accrual returns are positively associated with future earnings, and convey information about firms' future prospects. Our results are robust to several proxies for earnings smoothness, different estimation techniques, or various sets of control variables. We control for possible endogeneity problems by using three stages least squares (3SLS) and a system of simultaneous equations. The results obtained from 3SLS also support our results. We also re-examine our results by using different proxies of earnings smoothing, including the ratio of standard deviation of cash flows to standard deviation of net income, and the correlation between accrual and cash flows. Our results are robust to these sensitivity tests.

We examine future stock returns and operating performance for SEO firms by calculating portfolio-matched buy-and-hold (*BHAR*) and cumulative (*CARs*) abnormal returns for 6, 12, 18, and 36 months after the issuing year. The results show that firms with a higher level of earnings smoothing have higher *ROA* and *EPS* in every year over the three years following SEOs than those with a lower level of earnings smoothing. The differences in *ROA* and *EPS* between the two groups of firms are statistically significant. The findings are consistent with our prediction that only high quality firms, which anticipate high levels of future cash flows, are able to actively engage in smooth earnings over a long period of time prior to SEOs, thereby resulting in a lower degree of SEO underpricing through the SEO episode.

The remainder of this chapter is organized as follows. Section 2.2 provides related literature and motivation. Section 2.3 describes the research design and our SEO sample. Section 2.4 presents our empirical results around the SEO episode and Section 2.5 the empirical results

for the post-SEO stock returns and operating performance. Section 2.6 presents the results from various robustness tests. Section 2.7 concludes the chapter.

2.2 Related Literature and Motivation

Research supporting the managerial opportunism hypothesis shows that managers may smooth earnings to meet the bonus target (Healy, 1985), to protect their job (Arya et al., 1998), and/or to inflate earnings before exercising stock options (Bergstresser and Philippon, 2006). Those supporting the information revealing hypothesis show that firms smooth earnings to lower their cost of equity and risk perceptions of investors, and signal high future performance and high quality of earnings.

Theoretical models have attempted to explain why smooth earnings help reveal information about firms' future prospects. Channey and Lewis (1995) develop a model in which high quality firms convey their future earnings through smooth earnings. They show that, with asymmetric information, high quality firms inflate income in their financial reports more than low quality firms and that the former smooth earnings whereas the latter do not. In this model, high quality firms bear the cost of over reporting current period income via a tax burden to separate themselves from low quality firms, given that low quality firms are presumed unable to bear this burden. Only high quality firms can reveal information about future earnings by smoothing earnings. Ronen and Sadan (1981), using Spencer's (1973) signaling framework, also argue that high quality firms with good future prospect are more likely to smooth their earnings in order to reveal their quality. This is not to say that low quality firms may not also inflate earnings before some specific corporate events such as mergers and acquisitions, but rather that they are unable to do so over a long period of time given their poor future earnings.

Graham et al. (2005) found that 97 percent of CFOs surveyed prefer smoothing earnings with the belief that they lower the cost of capital and lead to more precise analyst's earnings forecasts. Tucker and Zarowin (2006) find a positive association between the degree of earnings smoothing and future stock returns, and Rountree et al. (2008) find that investors place higher value, measured by Tobin's Q, on firms with smoother performance.

The existing literature suggests that the market can infer firm quality based on a firm smoothing its earnings over a number of years. The present research aims to see if this prospect can payoff for these firms when they engage in SEOs. We hypothesize that managers of high quality firms with long historical smooth performance are more likely to push up the offer price to maximize proceeds from equity offerings, such that firms with smooth earnings are more likely to experience a lower degree of SEO underpricing episodes, compared with firms that do not.

The SEO underpricing literature is extensive. Corwin (2003) finds that SEOs are more underpriced for firms with high price uncertainty and bigger offer sizes. Kim and Shin (2004) find, investigating short selling and underpricing, that offer discounts are negatively related to underwriter rank and positively related to return volatility and underwriter spread. Cotton et al. (2004) documents that price stabilization is negatively associated with trading volume, offer price, and return variance.

More recently, Kim and Park (2005) examine the relation between earnings management by SEO firms and their offer prices. They find that SEO firms that aggressively manage earnings are also more likely to push up their offer prices and reduce the degree of underpricing. But in contrast to the present research, they do not test for the relationship between earnings smoothing and SEO underpricing. The longer term dimension of earnings smoothing suggests that it may be

reasonable to believe that firms that smooth rather than manage earnings may have better longer-term prospects. Therefore we also test, beyond Kim and Park (2005), whether firms that engage in long-term earnings smoothing prior to SEOs have higher stock returns and operating performance in the three years after the SEOs, compared to those that do not or that engage in shorter-term window dressing by managing earnings (before SEOs). This additional test aims to disentangle alternative explanations of managerial opportunism versus information effectiveness for long term earnings smoothing absent in Kim and Park (2005).

Indeed, the effects of smoothing performance on underpricing through SEO episodes have not received much attention. To our knowledge, no empirical research to date directly examines the relation between smooth performance and SEO underpricing. The objective of this chapter is to fill this gap in the literature using a large sample of seasonal equity offerings from the last two decades, and provide new evidence on the determinants of SEO undepricing.

2.3 Sample Description and Methodology

In this section, sample construction and offer date correction are discussed.

2.3.1 Sample Construction and Offer Date Correction

The 1989-2009 sample of U.S. common stock seasoned equity offerings (SEOs) by non-regulated companies comes from the Securities Data Company's (SDC) New Issue Database. The sample excludes initial public offerings and issues by non-U.S firms, as well as utilities and financial firms. Only offerings after 1989 are considered because the 1987 SFAS No.95 mandated that firms provide cash flow statement in their financial reports.

The initial sample consisted of 6,859 offerings, with stock prices obtained from the Center for Research in Security Prices (CRSP) and accounting variables from Compustat. For an offering to enter the final sample, it was necessary that there be at least 8 quarterly accounting

data points prior to the SEO, 250 prior trading days and 12 prior monthly returns, and sufficient other data to compute discretionary accruals. All sample firms were listed on the NYSE, NASDAQ, or AMEX. The methodology section explains in more detail where missing values necessary for obtaining discretionary accruals required us to eliminate firms from the sample. The sample size after these restrictions and deletions consists of 5,108 offerings.

Ritter's reputation rank for each underwriter, obtained from Jay Ritter's website, supplements the data for our SEO sample[2]. Ritter evaluates each underwriter's reputation based on scores ranging from 0 to 9 (highest quality). We use each SEO lead manager's name as the identifier to obtain the Ritter underwriter ranking scores. The merging process reduces the SEO sample to 3,156 offerings. Then, to avoid the effects of outliers, we winsorize the top and bottom 1 percent of the distributions of all variables. The final sample size consists of 2004 firms with 3,034 offerings.

Prior studies (Lease, Masulis, and Page (1991), Eckbo and Masulis (1992)) show that offer dates directly obtained from the SDC database are often inappropriate for analyzing the underpricing of SEOs due to the fact that some offers take place after the close of trading. For example, Lease et al. (1991) investigate the time stamp from the Dow Jones News Service (DNJS) and find that 25% of offers from 1981 through 1983 take place after the close of trading. To address this issue, researchers have corrected offer dates for their analysis by applying a volume based correction method. For example, Safieddine and Wilhelm (1996) apply this method and find that 18.4 % of offers during 1980-1991 required an offer date correction. Following their method, we adjust our sample offer date as follows: If trading volume on the day following the SDC offer date is (1) more than twice the trading volume on the SDC offer date,

2 Jay Ritter website at http://bear.warrington.ufl.edu/ritter/ipodata.htm

and (2) more than twice the average daily trading volume over the previous 250 trading days, then the day following the SDC offer date is designated as the offer date.

2.3.2 Control Variables

Prior studies document that the major determinants of SEO underpricing include the level of information asymmetry, level of uncertainty about firm value, underwriter reputation, price uncertainty, relative offer size, and conventional underwriter pricing practices (Altinkilic and Hansen, 2002; Corwin, 2003; Kim and Park, 2005). These variables also used in this paper, are defined as follows (see the appendix 1 for full descriptions).

Underpricing, the dependent variable in our multivariate analysis, is the closing price on the offer day (CRSP: PRC) minus the offer price, divided by the offer price. An alternative definition for our robustness tests is the closing price on the day prior to the offer minus the offer price, divided by the closing price on the day prior to the offer. Earnings smoothness, *Smooth*, is the ratio of the standard deviation of net income ([COMPUSTAT: IBQ] divided by the standard deviation of cash flows from operation (defined as [COMPUSTAT: IBQ] minus accruals [COMPUSTAT: ΔACTQ- ΔCHEQ- ΔLCTQ+ΔDLCQ-DPQ]) (both scaled by average total assets (COMPUSTAT: ATQ)). The volatility of net income is scaled by cash flow volatility in *Smooth* to measure the extent to which accruals are possibly used to smooth out the underlying volatility of the firm's operation, with higher values of this variable indicating more earnings volatility. We expect a negative coefficient for *Smooth*. The standard deviation of operating cash flows and net income are measured over twelve consecutive quarters, with a required minimum of eight quarters. Our measure of *Smooth* is similar to that used in prior research (e.g., Leuz et al., 2003; Francis et al., 2006; McInnis, 2010). Our primary measure of net income is net income before extraordinary item (COMPUSTAT: IBQ). Cash flows equal net income less accruals.

Accruals are the change in current assets (COMPUSTAT: ACTQ) minus the change in cash (COMPUSTAT: CHEQ) minus the change in current liabilities (COMPUSTAT: LCTQ) plus the change in shorter term debt (COMP: DLCQ) minus depreciation (COMPUSTAT: DPQ).

Stock price uncertainty, *Volatility*, is defined as the standard deviation of stock returns (CRSP: RET) over the period of 30 trading days ending 10 days prior to the offer date. Corwin (2003) finds that underpricing is associated with stock return volatility and bid-ask spread, and many studies show that higher return volatility is associated with higher levels of underpricing. We expect a positive coefficient for *Volatility*.

The effect of pre-offer price run up is controlled with the variable *PreCar*, calculated as the cumulative adjusted return over the period of five trading days prior to the offer. Loughran and Ritter (2002) show that equity issuers are more tolerant of excessive underpricing if they simultaneously learn about a post market valuation that is higher than what they expected. This suggests that issuers don't need much bargaining effort in their negotiations over the offer price with their contracted underwriters if they see the greater recent increase in their stock price. This also implies that pre-offer abnormal stock returns are positively related to the magnitude of the SEO underpricing. Thus, we expect a positive coefficient for *PreCar*. We follow Corwin (2003) to control for the effects of price pressure with the variable *Offersize,* calculated as shares offered divided by the total number of shares outstanding prior to the offer. Consistent with prior studies, we expect *Offersize* to be positively related to underpricing.

Prior studies also find that conventional underwriter pricing practice may have an important effect on SEO underpricing. Mola and Louran (2001) find that SEOs are clustered at integers and do not tend to fall on odd eight fractions. Harris (1991) and Ball et al. (1985) argue that rounded prices may reflect underwriter desire to reduce the costs of negotiating the offer

price and uncertainty about the underlying security's value. Such rounding practices may reflect the imprecise nature of the pricing process. Therefore, we include the control variable, *Tick*, which is a dummy variable equal to one if the decimal portion of the closing price on the day prior to the offer is less than $ 0.25, and zero otherwise. We also add the incremental variable *Ln(price)* and the interaction term, *Ln (price)*Tick* to our base regression model. Based on Corwin (2003), the sign of coefficients on *Ln (price)*Tick* and *Ln (price)* are expected to be negative and positive, respectively.

Previous studies document that NASDAQ issues are more underpriced than NYSE issues (Ritter and Welch, 2002) because of difference in trading practices. The dummy variable *Nasdaq*, equal to one if the issuer was listed on NASDAQ, and zero if on NYSE or AMEX at the time of offer, controls for this effect. We also include the variable *IPOUnderpricing* in our regressions, measured as the average underpricing across all IPOs during the same month as the SEO , where the monthly IPO underpricing estimates are obtained from Jay Ritter's website.

The effect of underwriter reputation on SEO underpricing is measured by the lead underwriter's ranking, also obtained from Jay Ritter's website. Ritter refines Carter and Manaster's (1990) ranking method to construct a new ranking database for major underwriters, with rankings based on a 0-9 scale, from 1.0 to 9.0. Our final control variables are the firm's risk (*Beta*), firm's size (*Size*, log of market value of equity ([CRSP: CHSO] multiplied by [CRSP: PRC)), and book to market (*BM*, log of the ratio of book value of equity (COMPUSTAT: CEQQ) to *Size*). We calculate beta from the regression of a firms' monthly raw returns on the monthly value-weighted market returns over the rolling five year window ending in the current fiscal year of the offer date.

2.3.3 Descriptive Statistics

Table 2.1 summarizes the characteristics of our sample SEOs. Table 2.1, Panel A presents the descriptive statistics for the sample firms. Our sample firms have a $632.76 million mean value of assets and $750.2 million mean equity market value. The average offering proceeds for the whole sample is $126.8 million. On average, our sample's return on asset ratio is -0.0086 (median of 0.007) and earnings per share is 0.037 (median of 0.06). The mean and median of market to book ratio is 0.49 and 0.36 respectively.

Table 2.1, Panel B presents the descriptive statistic for selected variables for the full SEO sample during the entire 1989-2009 period. We define underpricing as the closing price on the offer day minus the offer price, divided by the offer price.[3] The mean (median) value of the underpricing variable is 0.027 (0.013), which is statistically significant. The average underpricing is equal to 2.7% of the offer price for the sample period. The mean and median net income volatility is significantly lower than cash flow volatility. The mean (median) net income volatility is 0.035 (0.018) versus 0.062 (0.046) for cash flow volatility. Recall that given our definition of *Smooth*, the higher value of net income volatility relative to cash flow volatility, the lower the level of smoothing. The mean and median values of *Smooth* are 0.540 and 0.459 respectively. Stock return volatility during a 30 day period ending 11 days before the offer date is 0.033. A typical sample offer size is relatively large. The mean (median) of the relative offer size, calculated as the ratio of the number of offered shares to the total shares outstanding prior to the offer, is 0.249 (median of 0.18) or about 25% of shares outstanding.

Table 2.1, Panel C reports the offers' characteristics across exchange markets. Consistent with prior research, the degree of underpricing for NASDAQ offers is higher than NYSE and

[3] We also use the closing price on the day prior to the offer minus the offer price, divided by the closing price on the day prior to the offer, as an alternative definition in our robustness tests.

AMEX offers. The mean (median) for SEO underpricing is 0.034 (0.022) for NASDAQ and 0.018 (0.007) for NYSE and AMEX offers, with the mean differences statistically significant (*t*-value equal to -10.48). This is also the case for the volatility of cash flow and of net income. Generally, NASDAQ offers have higher levels of return volatility, net income volatility, and cash flow volatility than other exchange markets.

Table 2.1 Summary Statistics

This table presents descriptive statistics for our sample of firms and our sample of SEOs. The sample contains all SEO firms with available annual and quarterly data and matching data on CRSP during 1989-2009. The final sample consists of 2,004 firms with a total of 3,034 SEOs during 1989-2009. All variables are described in the appendix 1.

Panel A: Descriptive Statistics on Sample-Firms (N=2,004 firms)

Variable	Mean	Std.	25%	Median	75%
Total Assets (M$)	632.76	2520	27.87	82.23	325.0
Equity Market Value (M$)	750.2	3663	43.33	122.7	378.9
Return on Assets(*ROA*)	-0.008	0.101	-0.016	0.007	0.021
Firm specific risk (*Beta*)	1.397	1.081	0.781	1.281	1.91
Earnings per share (*EPS*)	0.037	3.00	-0.100	0.063	0.241
Book to market (*BM*)	0.491	0.537	0.231	0.366	0.582

Panel B: Descriptive Statistics on Sample-SEOs (N=3,034 SEOs)

Variable	Mean	Std.	25%	Median	75%
SEO Underpricing (*Underpricing*)	0.027	0.045	0.000	0.013	0.049
IPO Underpricing (*IPOunderpricing*)	0.195	0.193	0.097	0.149	0.202
Offer proceeds (mil.)	126.8	209.5	35.00	67.40	132.0
Relative offer size (%) (*Offersize*)	0.249	0.343	0.112	0.180	0.287
Smoothness (*Smooth*)	0.540	0.356	0.239	0.459	0.811
Volatility of net income (std. dev.)	0.035	0.068	0.009	0.018	0.040
Volatility of cash flow (std. dev.)	0.062	0.072	0.029	0.046	0.075
Volatility of returns (*Volatility*)	0.033	0.017	0.021	0.029	0.040

Panel C: Descriptive Statistics for SEOs across Markets (N=3,034 SEOs)

Variable	NASDAQ (N=1785)		NYSE and AMEX (N=1249)		*t-Test*	
	Mean	Median	Mean	Median	*t*-Statistics	*p*-Value
SEO Underpricing (*Underpricing*)	0.0348	0.0225	0.0184	0.0071	-10.48	0.000
IPO Underpricing (*IPOunderpricing*)	0.2036	0.1497	0.1794	0.2347	-3.48	0.000
Relative offer size(%) (*Offersize*)	0.2585	0.1971	0.2347	0.1563	-1.74	0.081
Return on Assets (*ROA*)	-0.0164	0.0026	0.0043	0.0104	6.64	0.000
Volatility of net income (std. dev.)	0.0447	0.0247	0.0217	0.0128	-10.60	0.000
Volatility of cash flow (std.dev.)	0.0718	0.0526	0.0499	0.0368	-8.98	0.000
Volatility of returns (*Volatility*)	0.0385	0.0343	0.0252	0.0228	-23.41	0.000

Table 2.2 reports Pearson correlations among the control variables to show whether the correlations are generally consistent with our predictions. Our main variable of interest, *Smooth*, where low values of *Smooth* indicate higher smoothing, appears to be significantly positively associated with the level of SEO underpricing (ρ=0.094, p<0.01). It appears that higher smoothing via accruals is associated with a lower levels of SEO underpricing, or *Underpricing* tends to be larger the greater the degree of earnings volatility.

We find no significant correlation between *Underpricing* and *Firmsize* suggesting that firm's size, on average, is not associated with the level of underpricing. However, relative offer size (*Offersize*) and volatility of returns (*Volatility)* are positively associated with *Underpricing* *(*ρ=0.029, p<0.01 *and* ρ=0.166, p<0.01*)*, possibly reflecting the effects of price pressure on SEO underpricing. We also find, consistent with earlier findings, that high reputation of underwriters is negatively related to the level of underpricing (-0.153), and that higher pre-offer price run-ups are positively related to the level of underpricing. The correlations generally support our prediction that firms with smooth earnings are more likely to experience a lower degree of SEO underpricing.

Table 2.2 Spearman Correlation

	Smooth	PreCAR	Beta	Underpricing	Rank	BM	Volatility	Firmsize	Offersize
Smooth	1								
PreCAR	-0.039	1							
	(0.029)								
Beta	0.184	-0.004	1						
	(0.001)	*(0.800)*							
Underpricing	0.094	0.437	0.060	1					
	(0.000)	*(0.000)*	*(0.000)*						
Rank	-0.052	-0.004	0.013	-0.153	1				
	(0.003)	*(0.808)*	*(0.442)*	*(0.000)*					
Volatility	0.230	-0.088	0.308	0.173	-0.198	1			
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*				
BM	-0.130	0.008	-0.202	-0.021	-0.043	-0.132	1		
	(0.000)	*(0.632)*	*(0.000)*	*(0.237)*	*(0.018)*	*(0.000)*			
Firmsize	0.017	0.035	-0.011	-0.130	0.496	-0.291	-0.246	1	
	(0.329)	*(0.051)*	*(0.532)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*		
Offersize	-0.051	-0.125	-0.063	0.114	-0.239	0.174	0.166	0.457	1
	(0.004)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	

2.4 Empirical Results around the SEO Episodes

2.4.1 Univariate Test

Table 2.3 presents the univariate tests results of the relation between earnings volatility and SEO underpricing for quintiles of earnings smoothness (Panel A) or underpricing (Panel B) in our sample, including *t*-statistics and *p*-values. Table 3, Panel A shows that both mean and median levels of SEO underpricing increase monotonically across earnings smoothness quintiles, with significant differences in the level of underpricing between firms with low versus high levels of earnings smoothing. Firms that smooth earnings heavily differ systematically from firms that smooth little or none at all. The mean of *Underpricing* in the lowest *Smooth* quintile are 0.0212, compared to 0.0343 in the highest quintiles, with the difference statistically significant at 1% (*p*-value <0.000). An average firm in the highest quintile of earnings smoothness may reduce underpricing by 0.33 dollars, which based on the average offerings per firm results in an increased value of $1.65 million, or 0.21 percent of firm value. This is a substantial increase in value that can be obtained from a smoothing earnings' strategy that, while relatively simple, is costly for underperforming firms to emulate. In addition, the univariate results show visible systematic patterns between *Smooth* quintiles and return on asset (*ROA*) and earnings per share (*EPS*), respectively. A close examination of Panel A reveals that there is a strong monotonic relation between level of earnings smoothing and *ROA* and *EPS* before SEOs. For example, the average *ROA* and *EPS* of firms in the highest level of earning smoothness quintile (lowest quintile of *Smooth*) are 0.016 and 0.211, respectively. These averages for firms in the lowest level of earnings smoothing (highest quintile of Smooth) are -0.046 and -0.128, respectively. The differences in the means (median) of *ROA* and *EPS* between the two bottom and two top *Smooth* quintiles are statically significant at 1 percent level**.** Also, consistent with

prior studies, variable *Rank* (*PreCar)* declines (increases) monotonically across earnings smoothness quintiles.

Table 2.3, Panel B shows results that are quantitatively similar to those in Table 3, Panel A, as Panel B also shows that there is a statistically significant difference in earnings smoothness between the lowest and the highest underpricing quintiles. Our univariate tests demonstrate a strong negative relation between earnings smoothness and SEO underpricing, and support our hypothesis that SEOs from firms with smooth performance are relatively less underpriced.

2.4.2 Multivariate Tests

The dependent variable is *Underpricing*, and the independent variable of interest is *Smooth* in the ordinary least squares regression results presented in this section. Our control variables for other factors widely accepted in the literature on the underpricing of SEOs s are (1) firm risk (*Beta*); (2) market to book (*BM*, using the ratio of the book value of total equity divided by the market value of total equity; (3) cumulative market adjusted returns prior to the offer date (*PreCar*); (4) IPO underpricing (*IPOUnderpricing)*; (5) return volatility (*Volatility*); (6) firm size (*Size*, the log of market equity); (7) relative offer size (*Offersize)*; underwriter's rank (*Rank*); (8) *Tick*; (9) *Ln(price*), and (10) the interaction term between *Tick* and *Ln(price)* (*Tick*Ln (price*)). We also use dummy variables (*Nasdaq*) to control for conventional pricing practices and the different characteristics of stock exchanges. Our regression takes the following general form.

$$\begin{aligned} Underpricing = {} & \alpha_0 + \alpha_1 Smooth + \alpha_2 Beta + \alpha_3 BM + \alpha_4 PreCar + \alpha_5 IPOunderpricing \\ & + \alpha_6 Volatility + \alpha_7 Size + \alpha_8 Offersize + \alpha_9 Rank + \alpha_{10} Tick + \alpha_{11} Ln(price) \\ & + \alpha_{12} Tick*Ln(Price) + \alpha_{13} Nasdaq + \varepsilon, \end{aligned} \tag{2.1}$$

Table 2.3 Univariate Analysis

This table presents univariate results. We group SEOs into quintiles based on their *Underpricing* and *Smooth*. Panel A reports mean of *Underpricin*g and other independent variables for earning smooth quintiles arranged from low to high. The difference in means of independent variables between the low and high quintiles is shown at the bottom of the table along with the associated *p*-values in parentheses. Panel B presents results sorting on *Underpricing* quintiles. All variables are described in the appendix 1 . Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A: Quintiles Based on *Smooth*

	Underpricing	PreCar	Beta	Volatility	BM	Rank	IPOUnderpricing
Low	0.0212	-0.017	1.272	0.2830	0.527	8.126	0.177
2	0.0230	-0.023	1.247	0.0296	0.502	8.032	0.184
3	0.0252	-0.026	1.243	0.0316	0.519	7.992	0.197
4	0.0333	-0.027	1.554	0.0368	0.493	7.885	0.214
High	0.0343	-0.034	1.846	0.0391	0.433	7.879	0.201
Difference (Low-High)	-0.0131***	0.017**	-0.574***	-0.010***	0.094***	0.152**	-0.024**
P-value	*(0.000)*	*(0.018)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.046)*	*(0.018)*

	ROA	EPS1	EPS2	EPSOP	Assets
Low	0.0162	0.2057	0.2031	0.2114	458.94
2	0.0125	0.1458	0.1567	0.1805	886.91
3	0.0032	0.0961	0.1089	0.1213	941.58
4	-0.0248	-0.2010	-0.2055	-0.0553	714.68
High	-0.0463	-0.0487	-0.0565	-0.1282	713.04
Difference (Low-High)	0.0625	0.2544	0.2596	0.3396	-254.1
P-value	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.000)*

Panel B: Quintiles Based on *Underpricing*							
	Smooth	PreCar	Beta	Volatility	BM	Rank	IPOUnderpricing
Low	0.5004	-0.0753	1.3990	0.0301	0.4932	8.2345	0.2012
2	0.5061	-0.0534	1.3720	0.0306	0.5138	8.1385	0.1960
3	0.5191	-0.0368	1.3968	0.0308	0.4975	8.1590	0.1825
4	0.5256	-0.0024	1.3577	0.0322	0.4914	7.8737	0.1814
High	0.6173	-0.0335	1.5116	0.0403	0.4805	7.5121	0.2143
Difference (Low-High)	-0.1169***	-0.0418***	-0.1126**	-0.0102***	0.0127	0.7224***	-0.0130
P-value	*(0.000)*	*(0.000)*	*(0.055)*	*(0.000)*	*(0.720)*	*(0.000)*	*(0.283)*

Table 2.4 Multivariate Analysis

The results shown in this table are based on the regressions using the ratio of standard deviation of net income to standard deviation of cash flow as a proxy for earnings smoothness. The table lists coefficients (*p*-values) from OLS regressions of underpricing on *Smooth*, defined as the ratio of standard deviation of net income to the standard deviation of cash flow, and a set of control variables. *P*-values are based on White's heteroskedasticity consistent standard errors. All variables are described in the appendix 1 . Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Intercept	0.0472***	0.0473***	0.0473***	0.0620***	0.0604***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Smooth	0.0080***	0.0077***	0.0078***	0.0050**	0.0050**
	(0.000)	*(0.000)*	*(0.000)*	*(0.018)*	*(0.019)*
Beta	0.0004		-0.0002	-0.0006	-0.0006
	(0.650)		*(0.792)*	*0.4378*	*(0.446)*
BM		-0.0019*	-0.0019**	-0.0018**	-0.0017*
		(0.068)	*(0.035)*	*(0.049)*	*(0.051)*
PreCar	0.1655***	0.1921***	0.1921***	0.2002***	0.2002***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
IPOUnderpricing	-0.0047	-0.0060	-0.0060	0.0013	0.0013
	(0.267)	*(0.171)*	*(0.169)*	*(0.761)*	*(0.759)*
Volatility	0.4596***	0.4626***	0.4652***	0.4329***	0.4340***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Size	-0.0008	-0.0010*	-0.0010*	-0.0003	-0.0003
	(0.106)	*(0.056)*	*(0.058)*	*(0.555)*	*(0.573)*
Offersize	0.0064***	0.0070***	0.0070***	0.0052**	0.0052**
	(0.009)	*(0.002)*	*(0.002)*	*(0.014)*	*(0.014)*
Rank	-0.0044***	-0.0044***	-0.0044***	-0.0032***	-0.0032***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Tick				0.0001	0.0063
				(0.917)	*(0.452)*
Ln(price)				-0.0084***	-0.0078***
				(0.000)	*(0.000)*
Ln(price)*Tick					-0.0020
					(0.431)
Nasdaq	0.0063***	0.0062***	0.0063***	0.0069***	0.0068***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*

The results support our hypotheses and consistent with its information role. The degree of SEO underpricing is negatively associated with earnings smoothness, with *Smooth* coefficient estimates ranging from 0.005 to 0.008 (p-value<0.000) across the five models. All regression specifications have high explanatory power (adjusted R-squares range from 0.24 to 0.28 and F-statistics are significant at 1%). The highly significant *Smooth* coefficients suggest that smooth performance improves information about future earnings, thereby leading to a lower degree of the SEO underpricing.

The coefficients of other control variables are also consistent with our expectations. For example, coefficient estimates on *PreCar, Offersize, Rank*, and *Nasdaq* are of the expected sign and statistically significant at conventional levels. In Models 3, 4, and 5 (Table 2.4), we **s**equentially add *Tick, Ln (price)* and the interaction term *Tick*Ln(price)* to the base model, with consistent results between these Models and Models 1 and 2. All coefficients for *Smooth* are positively related to the degree of underpricing, and other coefficient estimates are of predicted signs.

The coefficient on relative offer size (*Offersize*), with a magnitude of between 0.0052 and 0.007, is negative and significant at conventional levels in all model specifications, supporting the existence of price pressure effects on the degree of SEO underpricing. The coefficients on *BM* across all models are negative and statistically significant. This implies that high book-to-market firms experience a lower degree of SEO underpricing than low book-to-market firms. The coefficients on *Beta*, ranging from -0.0006 to 0.0004, are not statistically significant, suggesting that firm beta does not impact SEO underpricing. The coefficients of underwriter's rank, ranging from -0.0044 to -0.0032, are significant at the 1 % level in all specifications, suggesting that underwriter's reputation plays an important role in reducing the level of

underpricing. The coefficients on *Tick<0.25* are consistently positive, suggesting that offers are more underpriced when the previous days' closing price does not fall on an even dollar amount or $0.25 price increment. The results support the hypothesis that pricing practice is an important factor affecting the level of SEO underpricing. In model 5, the coefficient on *PreCar* is 0.2 (*p*-value<0.001), suggesting that large positive pre-offer returns lead to more underpricing. Unlike prior studies (e.g., Corwin, 2003; Kim and Park, 2005), the coefficients on *IPOUnderpricing* are not statistically significant in our models, implying that SEO underpricing is not related to IPO underpricing. In addition, the coefficients on dummy variable *Nasdaq* are significantly positive, showing that firms listed on NASDAQ have a greater degree of underpricing.

2.4.3 Three Stage Least Squares (3SLS) Estimation Results

Possibly, the results may be biased if earnings smoothing, pre-offer stock returns, and SEO underpricing are jointly and endogenously determined. To address this problem, we examine the relationship between SEO underpricing and earnings smoothness by estimating the following system of simultaneous equations using three stage least squares (3SLS) in the spirit of Kim and Park (2005)[4].

$$Underpricing = \alpha_0 + \alpha_1 Smooth + \alpha_2 DA + \alpha_3 PreCar + \alpha_4 Volatility + \alpha_5 IPOunderpricing$$
$$+ \alpha_6 Offersize + \alpha_7 BM + \alpha_8 Rank + \alpha_9 Tick + \alpha_{10} Lnprc + \alpha_{11} Lnprc\_tick + \alpha_{12} Nasdaq + \varepsilon. \quad (2.2)$$

$$Smooth = \alpha_0 + \alpha_1 Underpricing + \alpha_2 DA + \alpha_3 PreCar + \alpha_4 Offersize + \alpha_5 BM + \alpha_6 Total\_accrual$$
$$+ \alpha_7 Size + \varepsilon, \quad (2.3)$$

$$PreCar = \alpha_0 + \alpha_1 Underpricing + \alpha_2 DA + \alpha_3 Volatility + \alpha_4 BM + \alpha_5 Rank + \alpha_6 Size + \alpha_7 Beta$$
$$+ \alpha_8 Nasdaq + \varepsilon, \quad (2.4)$$

We anticipate the following signs in this system. Prior studies [e.g., Shipper (1989) and

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[4] Unlike Kim and Park (2005), we conduct Basman' (1960) test to check the validity of overidentifying restrictions in our 3SLS model specification. The Basman's statistics provided by the test (via SAS Proc Syslin 3SLS with option/overid) fails to reject the null hypothesis, with *F*-value=1.53 and *p*-value>0.2168.

Bethel and Krigman (2009)] show that the likelihood that managers of SEO firms engage in earnings management is higher the greater the level of information asymmetry. It follows that the higher the stock volatility prior to an SEO, the higher the SEO underpricing. Outside investors discount the share prices of firms with high levels of information asymmetry knowing that their managers are more likely to engage in window dressing prior to equity offerings. We expect a positive sign for the coefficient on *Volatility* in equation (2.2).

Low quality firms that intensively use discretionary accruals to inflate share prices prior to SEOs experience a high level of SEO underpricing, as such opportunistic behavior is more likely to be detected by outside investors or high quality auditors. Thus, the level of discretionary accruals is positively associated with SEO underpricing, such that we expect a positive sign for the coefficient on *DA* in equation (2.2)

Our argument that only high quality firms are able to smooth earnings over a long period of time before equity offerings to reduce underpricing suggests that the sign of the coefficient for *Smooth* in equation (2.2) is positive (the higher value of *Smooth*, the higher the earnings volatility). Corwin (2003) also shows that underpricing is positively related to large abnormal returns over the days prior to an SEO, such that we expect a positive coefficient on *PreCar* in equation (2.2).

If high quality firms can smooth earnings over a long period of time, then such firms are also more likely to experience larger pre-offer abnormal stock returns, suggesting a negative coefficient on *PreCar* in equation (2.3). If earnings smoothing conveys managers' private information about future earnings, then the coefficient on *Underpricing* in equation (2.3) should be positive, as firms with high levels of earnings smoothing prior to SEOs are more likely to experience a lower level of underpricing.

Finally, Gerard and Nanda (1993) find that pre-offer returns may reflect trading manipulation where managers may intentionally depress the stock price to exploit outside investors for the benefit of current shareholders through short selling around the SEO offer date. They provide evidence that a high level of short-selling around SEOs is positively associated with a high level of issue discounts, suggesting a negative coefficient on *Underpricing* in equation (2.4).

We measure discretionary accruals for year *t* as the residuals from the following cross section version of Jones model, modified by Kothari et al. (2005):

$$Accrual = \alpha_0 (1/Asset_{t-1}) + \alpha_1 * \Delta Sale_t + \alpha_2 \, PPE_t + \alpha_3 ROA + \mu_t \,, \qquad (2.5)$$

The total accrual (*Accrual*); change in sales ($\Delta Sale_t$); and gross property, plant, and equipment (*PPE*) are deflated by the average total assets (*Assets*) in this regression. The control variable *ROA* is added to the Jones model to account for the effect of firm performance because prior studies (Dechow et al., 1995; Kothari et al., 2005) find that the Jones model is misspecified for well performing or poorly performing firms. We estimate equation (2.5) by two-digit SIC code and fiscal year, and then obtain a firm's year *t* discretionary accruals by using the residuals from the estimated regression. In order to distinguish the effects of short-term earnings management (managerial opportunism) from long-term earnings smoothing (information informativeness) on SEO underpricing, we use the total discretionary accruals over one year prior to the offer date (*DA*), along with the *Smooth* variable in the 3SLS.

The results in Table 2.5 show that the coefficient on *Smooth* in (2.2) is significantly positive (0.0335, p-value<0.002), such that earnings smoothness is negatively associated with the degree of SEO underpricing, even after controlling for endogeneity via 3SLS. The *DA* coefficient in (2.2) is also significantly positive (0.0106, p-value <0.05).

Table 2.5 Three-Stage Least Squares Estimation on the Relation Between Earnings Smoothing and SEO Underpricing.

This table presents results from the system of simultaneous equations as follows:

$Underpricing = \alpha_0 + \alpha_1 Smooth + \alpha_2 DA + \alpha_3 PreCar + \alpha_4 Volatility + \alpha_5 IPOunderpricing + \alpha_6 Offersize + \alpha_7 BM + \alpha_8 Rank + \alpha_9 Tick + \alpha_{10} Lnprc + \alpha_{11} Lnprc\_tick + \alpha_{12} Nasdaq + \varepsilon,$

$Smooth = \alpha_0 + \alpha_1 Underpricing + \alpha_2 DA + \alpha_3 PreCar + \alpha_4 Offersize + \alpha_5 BM + \alpha_6 Total\_accrual + \alpha_7 Size + \varepsilon,$

$PreCar = \alpha_0 + \alpha_1 Underpricing + \alpha_2 DA + \alpha_3 Volatility + \alpha_4 BM + \alpha_5 Rank + \alpha_6 Size + \alpha_7 Beta + \alpha_8 Nasdaq + \varepsilon,$

Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Underpricing (2.2)	**Smooth (2.3)**	**PreCar (2.4)**
Intercept	-0.3885**	3.4370***	1.2506***
	(0.0027)	*(0.000)*	*(0.000)*
Underpricing		6.1709***	-5.0641***
		(0.000)	*(0.0011)*
Smooth	0.0335***		
	(0.0020)		
DA	0.0106**	-0.3175***	-0.0102
	(0.0384)	*(0.000)*	*(0.4610)*
PreCar	0.4245***	-3.1818***	
	(0.001)	*(0.000)*	
Volatility	0.4410***		1.0754
	(0.000)		*(0.1086)*
IPOunderpricing	0.0045		
	(0.1237)		
Offersize	0.0363***	-0.3795	
	(0.000)	*(0.000)*	
BM	-0.0012	0.0096	-0.0015
	(0.1579)	*(0.3285)*	*(0.8023)*
Rank	-0.0015**		-0.0230***
	(0.0497)		*(0.0045)*
Total_accrual		-0.0013*	
		(0.0869)	
Tick	0.0064*		
	(0.0664)		
Lnprc	-0.0107***		
	(0.0003)		
Lnprc_tick	-0.0015		
	(0.1712)		
Size		0.0202***	-0.0045
		(0.000)	*(0.1853)*
Beta			0.0087
			(0.1206)
Nasdaq	0.0057***		0.0334**
	(0.000)		*(0.0239)*
System Adj. R^2 0.1786	Basmann's (1960) test (F=1.53 p-value>0.2168)		

The significant coefficient on *DA* suggests that earnings management via discretionary accruals one year prior to the SEO has a significant effect on SEO underpricing, consistent with prior studies (e.g., Kim and Park (2005). As predicted, the coefficient on *PreCar* in (2.2) is positive and statistically significant (0.4245, p-value<0.001). This suggests that the existence of abnormal stock returns prior to the offer date also plays a significant role in the underpricing of an SEO (after controlling for endogeneity). Consistent with our prediction, the coefficient for *Volatility* is significantly positive in (2.2), with a magnitude of 0.4410, suggesting that higher level of information asymmetry leads to a higher degree of SEO underpricing. The results in Table 2.5 also show that the coefficients of *DA and Total_accrual* in (2.3) are statistically significant, with a magnitude of -0.3175 (p-value<0.000) and -0.0013 (p-value<0.086), respectively, implying that firms do smooth earnings via discretionary accruals. This also suggests that SEO firms are more likely to intensively use discretionary accruals in the year prior to equity offerings. Consistent with our prediRction based on Gerard and Nanda's (1993) manipulative trading hypothesis, the coefficient on *Underpricing* in (2.4) is statistically significantly negative (5.0641, p-value<0.001). This suggests that insiders may manipulate share prices through short selling activity, thereby leading to a lower level of pre-SEO returns. Overall, we find clear evidence that earnings smoothness results in a lower degree of SEO underpricing, even after controlling for possible endogeneity.

2.4.4 Cash Flow Volatility versus Accrual Volatility

Thus far, we have shown that earnings smoothness is negatively associated with SEO underpricing, and more consistent with the information revealing than the information garbling hypothesis. The former suggests that managerial discretion could enhance earnings'

informativeness through communication of private information (Watts and Zimmerman, 1986; Healy and Palepu, 1993; Subramanyam, 1996). Previous research also shows that accruals, on average, have incremental information content above that provided by cash flow (Bowen, Burghstahler, and Daley, 1987; Dechow, 1994). In this section, we examine whether cash flow volatility or accrual volatility has more pronounced effects on SEO underpricing, and how each of these incrementally contribute to the relationship between earnings smoothing and SEO underpricing.We decompose earnings volatility following Rountree et al. (2008) into cash flow volatility and accrual volatility, such that:

$$\delta^2_{Earnings} = \delta^2_{Cash\ flows} + \delta^2_{Accruals} + 2Cov(Cash\ flows, Accruals) \quad (2.6)$$

where accruals are constructed as earnings less cash flows as described in .

The results in Table 2.6 show regression estimates of *Underpricing* on earnings volatility and each of its components. The results as expected support the information revealing hypothesis, implying that *Accrual volatility* has a strong negative relation to *SEO Underpricing.* The coefficient estimate of *Accrual volatility* in Model 3 is -0.0045 (*t*= -1.83), so that a negative 1% change in accrual volatility leads to positive 0.0045% change in SEO underpricing, , suggesting that smooth earnings via accruals adds value. The coefficient of *Accrual volatility* is statistically significant (at 10%), whereas the coefficient on *Cash flow volatility* is not, suggesting that earnings smoothing via accruals reduces SEO underpricing beyond the cash flow volatility.

Overall, the results in Table 2.6 show that earnings smoothing via accruals reveals information about the firms' future prospect, and that earnings smoothing via discretionary

accruals over a number of years prior to the offer date leads to a lower level of SEO underpricing.

Table 2.6 SEO Underpricing and Components of Earnings Volatility

This table presents results from cross sectional regressions of the *Underpricing* on each components of earnings volatility. The components of earnings volatility include accrual volatility, cash flow volatility, and the correlation of cash flows and accruals. *P*-values are reported beneath the coefficient estimates in parentheses. All variables are described in the appendix 1. Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Model	**(1)**	**(2)**	**(3)**
Intercept	0.0699***	0.0673***	0.0640***
	(0.000)	*(0.000)*	*(0.000)*
Ln(Earnings volatility)	0.0033***		0.0042***
	(0.001)		*(0.002)*
Ln (Accrual volatility)			-0.0045*
			(0.067)
Ln (Cashflow volatility)		0.0017	0.0026
		(0.115)	*(0.311)*
Correlation	-0.0020	0.0039*	-0.0067*
	(0.498)	*(0.087)*	*(0.079)*
Beta	-0.0002	-0.0001	-0.000
	(0.767)	*(0.861)*	*(0.803)*
PreCAR	0.1748***	0.1750***	0.1754***
	(0.000)	(0.000)	(0.000)
IPOUnderpricing	0.0017	0.0023	0.0018
	(0.648)	*(0.547)*	*(0.638)*
Rank	-0.0031***	-0.0032***	-0.0032***
	(0.000)	*(0.000)*	*(0.000)*
Volatility	0.4242***	0.4388***	0.4264***
	(0.000)	*(0.000)*	*(0.000)*
Offersize	0.0046**	0.0046**	0.0048**
	(0.029)	*(0.033)*	*(0.025)*
Tick	0.0096	0.0096	0.0099
	(0.163)	*(0.161)*	*(0.149)*
Ln(price)	-0.0066***	-0.0070***	-0.0066***
	(0.000)	*(0.000)*	*(0.000)*
Ln(price)*Tick	-0.0032	-0.0033	-0.0034
	(0.140)	*0.1374*	*0.1257*
Nasdaq	0.0063***	0.0067***	0.006 ***
	(0.000)	*(0.000)*	*(0.000)*
System Adj. R^2	0.244	0.246	0.247

2.5 Empirical Results on Post-SEO Market Returns and Operating Performance

2.5.1 Post-SEO Stock Returns Performance

We hypothesize that firms with high levels of earnings smoothing over long periods of time before SEOs have higher stock returns after SEOs, compared to firms with low levels of earnings smoothing, given that high quality firms with high anticipated future cash flows are more likely to actively engage in earnings smoothing prior to SEOs. We use multiple approaches widely used in the literature to calculate abnormal stock returns for both groups of firms over 6-months, and 1-, 2- and 3-year periods following SEOs, and *t*-tests to examine for significant differences. Specifically, we calculate for post-SEO periods (6, 12, 24 and 36 months) portfolio matched buy and hold abnormal returns (*BHARs*) and cumulative abnormal returns (*CARs*), such that:

$$BHAR_i = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{Benchmark,t}) \qquad (2.7)$$

where the mean is the weighted average of the firm's *BHARs*, or

$$\overline{BHAR} = \sum_{i=1}^{N} w_i . BHAR_i \quad \text{and} \quad CAR_{\mathrm{i}} = \sum_{\mathrm{t=1}}^{\mathrm{T}}(R_{it} - R_{Benchmark,t}) \qquad (2.8)$$

where $R_{Benchmark,t}$ is the returns on corresponding value weighted size/ book to market (*BM*) portfolio constructed by Fama and French (1993).

We apply the same portfolio matching procedure to calculate *BHAR* and *CAR* for each firm. Two sub-samples from our main SEO sample are created, with the high (low) quality sub-sample including only firms from the top (bottom) two *Smooth* quintiles. We match at the beginning of each offer year each firm in our two sub-samples to its corresponding portfolio out of 25 portfolios using the 5x5 Size/BM breakpoints from WRDS's Fama-French dataset. Delisted firms are retained during the post-SEO windows to avoid survivorship bias by including delisting returns and investing the proceeds in the matching size/BM portfolio. Following

Mitchell and Stafford (2000), we calculate the value weighted average of the individual *BHARs* based on market capitalization at the event year (offer year), scaled by the level of the CRSP value weighted weights at each point in time. This procedure avoids the issue arising from unstandardized value weights that would give more weight to the more recent observations.

Table 2.7 provides both *BHAR* and *CAR* results over different post-SEO window horizons. Both the high and low quality sub-samples of firms – the top and bottom two *Smooth* quintiles - outperform their benchmark portfolios by 5.6 to 10.36 percent (depending on use of the value weighted *BHAR* or *CAR*) during the first six months following SEOs. Not surprisingly, as well documented in the literature (e.g, Teoh et al., (1998), Loughran and Ritter (1997)), performance deteriorates over the first two years following SEOs, as shown in Panels A and B, although the high quality sub-sample outperforms the low-quality and the benchmark. For example, in the 36 month horizon, *BHARs* and *CARs* show that the high quality sub-sample outperforms the low quality by 34.72 percent (5.38 percent) on a value weighted *BHARs* (*CARs*) basis (*p*-value=0.000). The performance of the high quality sub-sample persistently increases over time, regardless of the measurement of abnormal returns used, whereas the low quality performance deteriorates after 18 months following the SEOs.

2.5.2 Post-SEO Operating Performance

We also examine, in addition to stock returns, whether the post-SEO operating performance measured by return on assets (*ROA*) and earnings per share (*EPS*) of firms with high level of earnings smoothing are higher than those with low levels. Table 2.7 Panel C shows *ROA* and *EPS* in the offer and next three post-offer years for the two sub-samples. In all post-offer years, *ROA* and *EPS* for the high (low) quality sub-samples are positive (negative), with the difference statistically significant. The differences in *ROA* (*EPS*) between the high quality and

low quality sub-samples are 0.22 (1.383), 0.184 (1.698), and 0.169 (2.562) percent in the three years after the issue year, respectively.

Overall, the results for post-SEO stock returns and operating performance provide evidence that managers of low quality firms may still benefit from misleading investors through short-term earning management tactics surrounding SEOs by lowering the offer price through SEO episodes. However, the performance of such firms would deteriorate in the long run. In contrast, high quality firms that are able to smooth earnings over a long time-period prior to SEOs not only experience a lower level of SEO undepricing, but also higher long run performance. This finding supports our argument that only high quality firms that anticipate large future cash flows are able to smooth earnings over a long period of time prior to SEOs and are more likely to push up their offer prices, thereby experiencing a lower level of SEO underpricing

Table 2.7 Post-SEO Performance

This table presents post-SEO stock returns performance for two groups of firms based on levels of earnings smoothing. Panel A shows the average compounded buy-and-hold abnormal returns (*BHARs*) for both groups over different horizons. Returns are compounded over 6, 12, 18, and 36 months after the offer date. Panel B presents cumulative abnormal returns (*CAR*s) for high and low quality firms. Two sided *p*-values from conventional means tests are shown in parentheses next to coefficients. All variables are described in the appendix 1. Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Month	**Firm Type**	**Panel A: Buy-and-Hold Abnormal Returns (*BHARs*)**				**Panel B: Cumulative Abnormal Returns (*CARs*)**			
		Equally-Weighted		Value-Weighted		Equally-Weighted		Value-Weighted	
		BHAR	*p*-value	BHAR	*p*-value	CAR	*p*-value	CAR	*p*-value
6	Low quality (the top two *Smooth* quintiles)	3.2903**	0.0509	6.4170***	(0.000)	2.9918***	0.0019	5.6571***	(0.000)
	High quality (the bottom two *Smooth* quintiles)	0.3351***	0.0018	10.3634***	(0.000)	2.8705**	0.0369	8.8890***	(0.000)
	Difference (Low-High)	*2.9552****	*(0.000)*	*-3.9466****	*(0.000)*	*0.1212****	*(0.000)*	*-3.2319****	*(0.000)*
12	Low quality (the top two *Smooth* quintiles)	3.2961*	0.0678	2.3583	0.1644	1.5446	0.3038	-1.4150	0.3769
	High quality (the bottom two *Smooth* quintiles)	2.4327	0.5641	10.3175***	(0.000)	-3.5694	0.1438	4.9259***	0.0036
	Difference (Low-High)	*0.8635****	*(0.000)*	*-7.9592****	*(0.000)*	*5.1130****	*(0.000)*	*-6.3409*	*0.2863*
18	Low quality (the top two *Smooth* quintiles)	0.8775	0.6959	-2.5727	0.1817	-0.4818	0.7907	-3.514***	0.0045
	High quality (the bottom two *Smooth* quintiles)	-2.2059	0.5520	1.0437	0.7675	0.5603	0.8219	-4.228**	0.0372
	Difference (Low-High)	*3.0834****	*(0.000)*	*-3.6164****	*(0.000)*	*-1.0421****	*(0.000)*	*0.7147****	*(0.000)*
36	Low quality (the top two *Smooth* quintiles)	-7.2301*	0.0801	-6.8072*	0.0543	-5.4059**	0.0268	-3.9882**	0.0480
	High quality (the bottom two *Smooth* quintiles)	17.9644***	0.0023	27.9135	0.2469	13.0883**	0.0113	1.3954	0.6337
	Difference (Low-High)	*-35.194****	*(0.000)*	*-34.721****	*(0.000)*	*-18.494****	*(0.000)*	*-5.383****	*(0.000)*
		Panel C: Post-SEO Operating Performance Metrics for Both Groups							
		Year 0 (Offer year)		Year 1		Year 2		Year 3	
		ROA	EPS	ROA	EPS	ROA	EPS	ROA	EPS
	Low quality (the top two *Smooth* quintiles)	-0.1065	-0.5296	-0.1833	-0.6472	-0.1677	-1.2972	-0.1524	-2.0509
	High quality (the bottom two *Smooth* quintiles)	0.0546	1.0069	0.0371	0.7362	0.0165	0.4016	0.0168	0.5121
	Difference (High-Low)	*0.161****	*1.536****	*0.220****	*1.383****	*0.184****	*1.698****	*0.169****	*2.562****

2.6. Robustness Tests

The results thus far use *Smooth* as the primary proxy for earnings smoothness. In this section, two proxies for earnings smoothness are used as robustness tests. In the first, we use the decile rank of the ratio of the standard deviation of net income to the standard deviation of cash flows. Table 2.8, Column 1 shows that this new measure of earnings smoothness (the decile rank of *Smooth*) is positively associated with *Underpricing* and significant at the 1% level (*0.0008, p-value=0.000*).

Leuz, Nanda, and Wysocki (2003) argue that firms may use accruals to report smoother earnings and conceal economic shocks to operating cash flow. A negative correlation between accruals and cash flow, in their view, more directly measures earnings smoothing via accruals. Thus, we use this correlation as proxy for earnings smoothness as a second robustness test. Following Leuz et al. (2003) and Barton (2001), we use the correlation between quarterly cash flows and accruals over the five-year period prior to the offer date. The results shown in Table 2.8, Column 2 suggest that the more negative the correlation between accruals and cash flows, the less the degree of SEO underpricing. [Underpricing increases as the correlation becomes more positive (less negative)].

As a final robustness test, we re-estimate our regression specifications with an alternative measure of underpricing (*Underpricing_discount*), defined as the closing price on the day prior to the offer minus the offer price, divided by the closing price on the day prior to offer. Table 2.9 shows that our main results remain unchanged.

Table 2.8 Robustness Regressions

The results tabulated in this table are based on the regressions using the decile rank of the ratio of the standard deviation of net income to the standard deviation of cash flow (model 1), and the correlation between cash flows and accruals (model 2) as proxies for earnings smoothness. *P*-values are reported beneath the coefficient estimates in parentheses. All variables are defined in the appendix 1. Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Dependent variable: *Underpricing*		
Model	**Model 1**	**Model 2**
Intercept	0.0582***	0.0667***
	(0.000)	*(0.000)*
Decile rank (*Smooth*) (model 1) Correlation (*Cashflow/Accruals*) (model 2)	0.0008***	0.0052**
	(0.0014)	*(0.033)*
Beta	-0.0009	-0.0006
	(0.341)	*(0.369)*
BM	-0.0017*	-0.0019**
	0.0903	*(0.037)*
PreCar	0.2023***	0.2035***
	(0.000)	*(0.000)*
IPOunderpricing	0.0009	0.0011
	(0.850)	*(0.761)*
Volatility	0.4401***	0.4464***
	(0.000)	*(0.000)*
Firmsize	-0.0002	-0.0002
	(0.705)	*(0.681)*
Offersize	0.0051**	0.0054**
	(0.016)	*(0.013)*
Rank	-0.0031***	-0.0034***
	(0.000)	*(0.000)*
Tick	0.0068	0.0051
	(0.420)	*(0.452)*
Ln(price)	-0.0078***	-0.0077***
	(0.000)	*(0.000)*
Ln(price)*Tick	-0.0024	-0.0018
	(0.359)	*(0.460)*
Nasdaq	0.0066***	0.0072***
	(0.000)	*(0.000)*
Adj. R^2	0.281	0.289

Table 2.9 Robustness Regressions (Continued)

This table presents results obtained from regressing *Underpricing_discount* on alternative proxies for smoothness, plus a set of control variables. *P*-values are reported beneath the coefficient estimates in parentheses. All variables are defined in the appendix 1. Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Dependent variable: *Underpricing_discount*			
Model	**(1)**	**(2)**	**(3)**
Intercept	0.0624***	0.0620***	0.0674***
	(0.000)	*(0.000)*	*(0.000)*
Smooth (model 1) Decile rank of *Smooth* (model 2) Correlation (*Cashflow/Accrual*) (model 3)	0.0038**	0.0005***	0.0037**
	(0.020)	*(0.004)*	*(0.033)*
Beta	0.0008	0.0008	0.0008
	(0.146)	*(0.156)*	*(0.154)*
BM	-0.0007	-0.0007	-0.0007
	(0.286)	*(0.283)*	*(0.288)*
PreCar	0.0764***	0.0764***	0.0765***
	(0.000)	*(0.000)*	*(0.000)*
IPOunderpricing	-0.0060**	-0.0062**	-0.0056**
	(0.041)	*(0.035)*	*(0.049)*
Volatility	0.3992***	0.0396***	0.4019***
	(0.000)	*(0.000)*	*(0.000)*
Firmsize	-0.0001	-0.0001	-0.0001
	(0.717)	(0.654)	*(0.7805)*
Offersize	0.0026*	0.0027*	0.0026*
	(0.098)	(0.093)	*(0.096)*
Rank	-0.0033***	-0.0033***	-0.0034***
	(0.000)	(0.000)	*(0.000)*
Tick	0.0041	0.0041	0.0040
	(0.429)	*(0.426)*	*(0.442)*
Ln(price)	-0.0087***	-0.0086***	-0.0087***
	(0.000)	*(0.000)*	*(0.000)*
Ln(price)*Tick	-0.0012	-0.0012	-0.0012
	(0.446)	*(0.445)*	*(0.457)*
Nasdaq	0.0034***	0.0033**	0.0034***
	(0.009)	*(0.011)*	*(0.009)*
Adj. R^2	0.267	0.268	0.267

2.7 Conclusion

This study examines the relation between earnings smoothing and SEO underpricing. We argue that high quality firms that expect larger quantity of cash flows in the near future are more likely to actively manage earnings via discretionary accrual before seasoned equity offerings to reduce the cost of capital and SEO underpricing. If high quality firms that are confident about future earnings actively smooth earnings, it is plausible to assume that they also push their offer prices up more aggressively.

In addition, market participants who observe a firm smoothing earnings over a number of years prior to an SEO are more likely able to infer firm quality, since smoothing over a longer period is more costly for lower quality firms. Taken together, we hypothesize that firms with smooth performance over a number of years prior to the SEOs would have a lesser degree of SEO underpricing.

Our empirical results support this hypothesis, such that earnings smoothness appears to result in less SEO underpricing, based on a sample of more than 3,000 SEOs from 1989 through 2009. This relationship holds regardless of estimation techniques, earnings smoothness proxies, or measures of SEO underpricing that are used. Three stage least squares estimation and other robustness tests also support our hypothesis, even after controlling for endogeneity problems. We also find evidence that firms with a long historical pattern of smooth earnings prior to SEOs significantly outperform on a stock returns and operating basis those with more volatile earnings in at least the three year period thereafter.

The economic significance of these results is such that smoothing reduces mean underpricing by $0.33 per share and increases the mean offering value by $1.65 million (about one-fifth of one percent of the mean offering firm’s value). A substantial increase in value is

possible utilizing a simple strategy that is nevertheless costly for underperforming firms, who suffer substantial opportunity losses from new equity offerings.

Chapter 3

Lines of Credit, Market Timing, and the Underpricing of Seasoned Equity Offerings

3.1 Introduction

In an efficient or frictionless capital market, firms theoretically should not worry about raising external capital to fund acceptable new projects. Such projects would attract capital whenever needed to maintain high levels of cash holdings to safeguard against liquidity shocks or future investment needs.

In the presence of inefficient markets with frictions, firms need to guard against liquidity shocks and maintain cash holding in order to honor their contractual obligations or to not bypass positive NPV projects. Cash holdings can provide firms with flexibility in their financing activity; high levels of cash holdings can also result in managerial entrenchment or wealth expropriation by managers (Jensen, 1986). To minimize the agency and managerial entrenchment problems, firms need to trade-off between the benefits and costs of holding cash by equating marginal benefits with marginal costs in their cash management decisions. One solution to these agency problems is for firms to obtain lines of credit, loan commitments or credit revolving facilities, from commercial banks for liquidity management. The literature on the role of lines of credit in liquidity management shows two major advantages. First, firms can use lines of credit as options to hedge against credit worthiness deterioration or credit rationing (e.g., Campell, 1978; Hawkins, 1982). Firms with lines of credit are theoretically allowed to borrow from a lender in any amount up to specific limit at the specified price (Duan and Yoon, 1993). As such, firms can reserve their unused lines of credit or committed loans as liquidity

insurance for future liquidity shocks. Second, firms facing high degrees of information asymmetry may see a line of credit as an optimal solution to cope with asymmetric information problems in non-cooperated games between borrowers and lenders (e.g., Thakor and Udell, 1987, Booth at al., 1991). By paying small upfront fees for committed loans, informationally problematic borrowers facing high costs of raising equity can use lines of credit as options to hedge against adverse liquidity shocks when valuable investment projects arise. As such, obtaining lines of credit instead of hoarding cash may reduce managerial agency free cash flow problems.

Bank lines of credit theoretically give firms flexibility in their financing decisions with regard to future projects. However, they are not a perfect substitute for cash, although lines of credit are preferred to cash, even though U.S. firms still hold significant amount of cash in their balance sheets (Bates et al, 2009). Bank loan commitments are usually contingent on firm performance and require a specified set of financial ratios. Firms that want to obtain lines of credit to guard against future liquidity shocks have to maintain their financial performance at a level required by their lenders, among which is a certain level of cash holdings. That is, credit lines are positively associated with the level of firm's cash holdings. For example, Sufi (2009) empirically shows that 87% of public firms in the U.S. have access to lines of credit, and that lines of credit and cash are not perfectly substitutable in liquidity management.

I am aware of no other studies that have investigated the effects of lines of credit on market timing and capital structure. Using line of credit information directly retrieved from filings on SEC's Edgar databases, I unveil a different role for lines of credit in creating more value for the firm. First, I document that firms accessing lines of credit are more active in marketing timing, compared to firms that don't access lines of credit. Using three measures that

capture market timing behavior, I find clear evidence that the capital structure of firms with lines of credit are affected more by market timing activity than the capital structure of similar firms without lines of credit. Interestingly, this finding is somewhat contrary to the conventional intuition that firms accessing lines of credit are more likely to use commercial loans for their financing needs, thus leading to a higher financial leverage.

Second, I posit that the effects of lines of credit on capital market timing depend on a firm's financial health. In the presence of financial constraints, there is a critical role for corporate liquidity policy, making the choice for cash and credit lines important. Generally, financially constrained firms find it difficult to raise external financing when they need to sponsor new investment opportunities. Higher cash holdings are more valuable for constrained firms than for unconstrained firms because constrained firms are more likely to rely on internal financing resources: cash flow and cash holdings as ways of preserving financial flexibility, given the high costs of external financing (e.g., Bate at al. (2006), Almeida, Campello, and Weisbach (2004), Almeida and Camplello (2010)). My second argument is simple. High cash holdings in constrained firms, particularly those without investment opportunities, may impede their market timing activities since the marginal benefit of additional cash holdings from timing equity offerings does not outweigh the costs of hoarding too much cash in terms of agency problems. In addition, I also argue that the role of lines of credit in market timing activity can be more pronounced for unconstrained firms that can relatively easily access to other source of funds, including external equity and cash flows. That is, unconstrained firms can use both lines of credit and cash holdings saved out of their cash flows as a buffer for temporary liquidity needs while waiting for the market to become more favorable for their new equity offerings. As such, lines of credit are not only used as options on liquidity to fund future investment opportunities,

but also as a vehicle to strategically pursue timing the equity market, especially for unconstrained firms. While it could be argued that all firms have incentives to take advantages of lines of credit to time their equity issues by postponing their offerings in unfavorable market conditions, financially constrained firms find it more difficult to time their equity issues since lines of credit are generally offered contingent on a certain threshold of cash holdings. That said, lines of credit are possibly much more valuable for unconstrained firms with respect to equity market timing. Thus, I analyze the impact of lines of credit on two separate subsamples: financially constrained and non-financially constrained. I sort firms into constrained and non-constrained samples based on different criteria widely accepted in the literature, including KZ index, Altman’s Z score, and Ohlson’s O-score. Under each of our three constraint criteria, I find that the impact of lines of credit on market timing is particularly strong for unconstrained firms while there is no impact at all of lines of credit on marketing timing for constrained firms.

Finally, I examine the roles of lines of credit in lowering the underpricing of seasoned equity offerings (SEOs). If firms accessing lines of credit are more active in market timing, then I also expect that such firms can delay equity offerings during the periods of unfavorable market conditions and conduct offerings when market conditions are more favorable, thereby leading to a lower degree of SEO underpricing. The results support my prediction, irrespective of which measure of underpricing I use.

I also perform two matched sample analyses to test robustness of my results. First, I randomly select 75 firms (about half of the non-credit line sample) and paired-match them to 75 firms in the credit-line sample with the same level of total assets, return on assets, tangible assets, and two-digit SIC code in their IPO years. The second method involves conducting the propensity score matching. I match 75 randomly selected firms in the non-credit line sample with

75 firms in the credit line sample on the basis of their propensity score, which is a measure of the firm's propensity to have a line of credit based on the firm's characteristics. The results based on matched sample analyses confirm our previous findings. That is, firms accessing lines of credit are more likely to engage in market timing and experience a lower degree of SEO underpricing.

Overall, this chapter looks at the role of lines of credit in a different perspective by examining the effects of lines of credit on market timing and SEO underpricing, thus enriching the current literature on capital structure, equity offerings, and lines of credit. The chapter not only provides insights on the roles of lines of credit in market timing activity, but also shed light on how lines of credit can create more value by lowering the level of underpricing through SEO episodes. This chapter proceeds as follows. Section 3.2 presents some related literature on the relationship between market timing and capital structure. Section 3.3 presents the method and our proxies for market timing. Section 3.4 provides evidence on the effects of lines of credit on capital structure and equity timing activity. Section 3.5 examines the effects of lines of credit on SEO underpricing. Section 3.6 discusses the robustness tests. Section 3.7 concludes the chapter.

3.2 Related Literature

In corporate finance, equity market timing can be understood as a corporate practice that allows firms to create more value by capturing their stocks' misvaluation. This suggests that firms are more likely to issue equity when their stocks are overvalued and repurchase when their stocks are undervalued (Myer and Majluf,1984, Lakonishok et al., 1994). As a result, firms may issue equity when this form of external capital is cheap even if the financing is not necessary. On the other hand, firms may not issue equity when they experience temporary liquidity shocks (Stein, 1996; Huang and Ritter, 2009). Instead, firms may use debts or short term borrowings to satisfy their immediate financing needs to delay equity issuances until favorable market

conditions appear. Graham and Harvey (2001) find that two thirds of the participants in an anonymous survey of 500 Fortune CFOs admit to market timing capital structure decisions, with an important factor being the amount by which their stocks are over or undervalued.

Subsequent studies on market timing such as those by Baker and Wurgler (2002), Gompers and Lerner (2003), and Kayhan and Titman (2007) document the prevalence of equity timing strategies with respect to capital structure decisions. Baker and Wurgler (2002) are the first among those supporting the market timing theory of capital structure by conducting a direct test on how market timing affects capital structure. They propose that current capital structure is the cumulative outcome of past attempts to time the market. To test this proposition, they construct a variable, namely "*external finance weighted average*" that measures the relevant historical valuation in market valuations. This variable takes high values when firms raise equity during periods of high market valuations (high market to book ratio) and low values during periods of low market valuations (low market to book ratio). This variable is used as a proxy for market timing for regression specifications that examine the effects of market timing on book value and market leverage. Since the authors control for current investment opportunities in the form of current market to book ratios in the regressions, the proxy variable "*external finance weighted average*" can pick up the transient market timing opportunities. Based on this novel proxy for market timing, Baker and Wurgler (2002) are able to show that firms do time the equity market such that the current capital structure is a cumulative outcome of a firm's past equity timing activities. Following these lines of argument, several researchers use more refined proxies for market timing to further investigate the effects of past equity market timing activity on capital structure. Their findings also provide evidence that market timing is one of the most important factors affecting capital structure decisions.

More recently, Huang and Ritter (2009) test the marketing timing theory of capital structure using variables that control for both the pecking order and static tradeoff hypothesis. They compare the cost of debt to the cost of equity, after controlling for time trend and other firm specific and macroeconomic conditions, and find that firms fund a large portion of a financing deficit with proceeds from equity offerings raised in years when the cost of equity is low. They also find that equity issuance has a persistent effect on capital structure for many years, such that firms adjust slowly toward their target leverage after equity issuance. Along these lines, Warr et al. (2012) find that firms take advantage of equity mispricing to accelerate adjustments toward leverage target when their equity is overpriced.

While the literature on liquidity management is vast, there are few studies focusing on lines of credit. Only recently, Sufi (2009) recognized this limitation and conducted the first empirical study on the role of credit lines on liquidity management. Lines of credit can theoretically be used as a substitute for cash to guard against liquidity shocks (Holmstrom and Tirole 1998; Boot et al., 1987), but empirical studies show that their role in liquidity management is not crucial as compared to that of cash holdings. Lines of credit may become a viable liquidity substitute for cash only for firms with high levels of cash flow, because lending banks usually employ minimum cash flow based financial covenants for firms to quality for lines of credit. Cash strapped firms therefore have difficulty initiating or renewing lines of credit. (Sufi, 2009). The purpose of the current research in the context of this literature is to understand why lines of credit, though not perfectly substitutable for cash, are valued differently in constrained and non-constrained firms relative to market timing. I examine whether lines of credit have effects on market timing and, if so, what are the differential effects of the timing behavior for constrained versus non-constrained firms.

3.3 Sample Description and Descriptive Statistics

3.3.1 Sample Construction

The data for this paper comes from several sources. First, I begin with the universe of all non-financial U.S. firms in Compustat from 1996 through 2006 for which I can identify their IPO dates from SDC platinum and Jay Ritter's IPO databases. I focus on the 1996-2006 periods due to the following reasons. First, the SEC has required that all firms submit their electronic filings to SEC's Edgar database since 1996, thereby allowing me to employ a text search algorithm (a web crawler) to retrieve information on lines of credit from annual 10-K filings. Second, I need to follow up firms for up to ten years after their IPOs to examine the evolution of their capital structures during the sample period. Third, I use a web crawler to search for firms' credit line information, but still need to engage in the time consuming process of manually reading data on the sample firms to confirm that the crawler correctly identified said firms. Finally, I check the results based on my dataset in a robustness test against those in the 1996-2002 dataset kindly provided by Prof. Sufi of the University of Chicago. I restrict my sample to firms that have at least four consecutive years of positive assets and book leverage over the sample period. I also exclude firms, following Baker and Wurgler (2002), with book value of assets below $10 million, and firms without complete total assets data between the IPO year and the year the firm exits Compustat. This filtering process leaves me with a sample of 1,017 firms with 9,391 firm year observations.

Next, much like Sufi (2009), I program a web crawler that searches every 10-K annual filing to identify a firm's access to a line of credit. Specifically, I link each firm year observation from our sample to its respective 10-Q or 10-K SEC filing through its CIK identifier provided by both SEC-Edgar and Compustat. The webcrawler searches for seven phrases that may identify

access to a line of credit in each firm's electronic filing on the SEC's Edgar database. The seven phrases are: "*lines of credit*," "*committed loans*," "*revolving credit facilities*," "*revolving credit agreement*," "*bank credit line*", "*credit lines*," and "*working capital facilities*". Whenever the program finds one of these search phrases, it retrieves related information such as the CIK or GVKEY from the filings and downloads the paragraph containing said phrases into an excel file. This information is then manually checked to avoid a Type I error, where the null hypothesis of no line of credit is rejected when in fact it is true. I create a dummy variable (*Linedummy*) that takes the value of 1 if a firm has a line of credit in a given year, and zero otherwise.

Using CIK identifier and links provided by the SEC on its website, the text search program identified 958 firms with 8,203 firm year observations for which information on lines of credit exists every year during the period 1996-2006. Due to missing data for my timing measures and control variables, and the requirement that the market-to-book ratio be less than 10, the usable size of the dataset for regression analysis consists of 568 firms with 5,216 firm year observations. I then split the full sample into two subsamples, the credit line and non-credit samples, depending on whether firms have a line of credit or how often they access their line of credit over the sample period. For the main regressions, I sort firms that do not have lines of credit in any year over the sample period and firms that have at least one year accessing lines of credit during the sample period into non-credit line and credit line samples, respectively. The first subsample, in which lines of credit are not available, consists of 145 firms, and the second subsample consists of 423 firms. For robustness, I classify firms that have lines of credit for less than three years over the 10-year sample period as non-credit line firms and firms accessing lines of credit more than two years over the 10-year sample period as credit line firms. This sorting

method leaves me 217 firms in the first sample and 351 firms in the second sample. I winsorize all variables in the regressions at the 1% and 99% levels to avoid outliers.

3.3.2 Descriptive Statistics

Table 3.1, Panel A presents descriptive statistics for the entire sample during 1996-2006. The average total asset for the firm year observations is $414.12 million. The average book leverage and market leverage are 0.489 and 2.65, respectively. While the mean EBITDA for the full sample is a negative 1.47 % at the total book assets, the median firm has operating earnings of 8.03 % of total assets. The mean and median of the market to book value ratio are 2.648 and 1.787, respectively.

Table 3.1 Summary Statistics

This table presents descriptive statistics for sample of firms with and without a line of credit during 1996-2006. The sample contains all firms with available annual data on Compustat data and matching data on SDC's IPO sample during 1996-2006. The final sample (after excluding financial firms, firms with book leverage greater than 1 and market to book greater than 10) consists of 568 firms with 5,216 firm year observations. Firms with minimum book assets below $10 million and firms without complete data on total assets between the IPO year and the year the firm exit Compustat are also excluded. Market-to-Book (*MB*) ratio is assets minus book equity plus market equity all divided by assets. Book leverage (*BL)* is book debt to assets (in percentage term). Market leverage (*ML*) is book debt divided by the result of total assets minus book equity plus market equity (in percentage term). *Tangibility* is total tangible assets include plant, property, and equipment. Profitability is defined as earnings before interest and debt divided by total assets. Capital expenditure (*Capex*) is the total capital expenditures divided by total assets.

Panel A: Descriptive Statistics on pooled sample (552 firms with 5,046 firm-year observations)

Variable	Mean	Std.	25%	Median	75%
Total Assets (M$)	414.117	1601.80	36.449	100.350	305.210
Market-to- Book (MB)	2.648	3.068	1.144	1.787	3.091
Tangibility(PPE)	99.146	347.238	3.669	14.22	60.286
Profitability(EBITDA/TA)	-0.0147	0.3911	-0.0635	0.0803	0.1541
Capital Expenditures (CAPEX/TA)	0.0645	0.0785	0.0194	0.0403	0.0783
Book Leverage (BL)	0.4887	0.6661	0.2081	0.3762	0.6019
Market Leverage (ML)	0.3016	0.2705	0.0784	0.2044	0.4791

Panel B: Descriptive Statistics on Line of Credit Sample (3,193 firm-years)

Variable	Mean	Std.	25%	Median	75%
Total Assets (M$)	473.482	1829.78	46.241	128.382	365.134
Market-to- Book (MB)	2.2302	2.3309	1.0449	1.5174	2.5555
Tangibility(PPE)	122.260	403.963	6.025	22.118	86.022
Profitability(EBITDA/TA)	0.0375	0.3110	0.0110	0.0987	0.1654
Capital Expenditures (CAPEX)	0.0691	0.0776	0.0229	0.0447	0.0857
Book Leverage (BL)	0.5012	0.5569	0.2590	0.4188	0.6370
Market Leverage (ML)	0.3495	0.2725	0.1130	0.2722	0.5480

Panel B: Descriptive Statistics on Non-Line of Credit Sample (145 firms with 1,353 firm-years)

Variable	Mean	Std.	25%	Median	75%
Total Assets (M$)	332.90	118.750	28.366	66.636	214.008
Market-to- Book (MB)	3.2212	1.4084	1.4081	2.2178	3.7735
Tangibility(PPE)	67.525	246.178	2.192	7.351	33.719
Profitability(EBITDA/TA)	-0.0863	0.4709	-0.1856	0.0333	0.1338
Capital Expenditures (CAPEX)	0.0581	0.0797	0.0159	0.0343	0.0699
Book Leverage (BL)	0.4715	0.1581	0.7911	0.3046	0.5778
Market Leverage (ML)	0.2359	0.2534	0.0504	0.1285	0.3422

I also partition firms in the full sample into two subsamples - line of credit and non-line of credit sub-samples. Table 3.1, Panels B and C, shows descriptive statistics for these sub-samples. The $473.48 million average total asset values for the credit line sub-sample is higher than the $332.90 million for the non-credit line sub-sample. Similarly, the average book leverage (market leverage) ratios of 0.5012 (0.4715) for the credit line sub-sample are higher than the 0.3016 (0.2359) for the non-credit line sub-sample. This suggests that firms accessing lines of credit depend more on commercial loans for their financing needs.

Credit line sample firms are also more profitable. The mean (median) of return on assets are 0.0375 (0.0987) for the credit line sub-sample and -0.0863 (0.0333) for the non- credit lines

sub-sample. Firms in the line of credit sub-sample have more tangible assets, on average, than firms in the non-credit line sub-sample, as the mean is 122.26 for the former versus 67.53 for the latter. Firms with credit lines have higher capital expenditures than firms without credit lines, consistent with the prior studies (e.g., Sufi, 2009) that profitable firms with high cash flow are critical to obtaining a line of credit.

3.4 Methodology

3.4.1 Proxies for Market Timing using Previous Mispricing Measures

I use two commonly adopted mispricing measures for our marketing timing variables. First, I follow Baker and Wurgler (2002) to construct a timing measure, which is the "*external finance weighted average market to book ratio-*$MBEFWA_{t-1}$". This measure captures market timing behavior such that firms are more likely to issue equity when their stock prices are high and issue debt when their stock prices are low. The main argument in Baker and Wurgler (2002) is that the fluctuations of market valuation, which can be observed by changes in the market-to-book ratio, have a long run impact on capital structure. Firms take advantage of "window of opportunities" or stock misvaluations by issuing both equity and/or debt, as appropriate, affecting capital structure. The Baker and Wurgler's (2002) mispricing timing measure (*BW_timing*) is defined as follows:

$$BW\_timing = MBEFWA_{t-1} = \sum_{s=0}^{t-1} \frac{EF_r}{\sum_{r=0}^{t-1} EF_r} (MB_s) \quad (3.1)$$

where 0 is the IPO year or the first year the firm entered Compustat; EF_s and MB_s denote the sum of net debt and equity issued and the market-to-book ratio, at time s; and *EF* is the sum of net equity and net debt issued. Net equity issue is defined as the change in book equity, minus the change in retained earnings, divided by total assets. Newly retained earnings are defined as the change in retained earnings divided by total assets. Net debt issue is defined as the residual

change in assets divided by total assets. Market value is defined as total assets minus the book value of equity plus the market value of equity.

Baker and Wurgler (2002) develop this measure of market timing based on traditional theories that view market-to-book ratios as the measure of investment opportunities and market misvaluations. Used as a proxy for equity mispricing; higher market-to-book ratios reflects higher equity mispricing. Firms seek lower costs of financing by raising equity when their market-to-book ratios are high and issuing debt when their market-to-book ratios are low. This measure will take high values for firms that raised external financing when the market-to-book was high and vice versa. Baker and Wurgler (2002) are also aware that market-to-book can capture investment prospects that lead to a negative relationship between capital structure and their proxy for market timing. They use the lagged one period market-to-book ratio in their regressions to control for the effects of investment opportunities.

Second, I follow Kayhan and Titman (2007) to construct a different proxy - the yearly market timing measure - for market timing. This new variable as argued by Kayhan and Titman (2007) is more effective than that of Baker and Wurgler (2002) in capturing a firm's timing behavior because the new measure excludes the average market to book ($\overline{M/B}$) embedded in the former measure that capture investment opportunities. Specifically, they suggest the following decomposition:

$$\sum_{s=0}^{t-1} \frac{EF_r}{\sum_{r=0}^{t-1} EF_r} (MB_r) = \frac{Cov\ (EF, M/B)}{\overline{EF}} + (\overline{M/B}) \tag{3.2}$$

$$\text{Yearly timing } (YT) = \left(\frac{\sum_{s=0}^{t-1} EF_s * (M/B)_s}{t}\right) - \overline{EF} * \overline{MB} = \text{Cov (EF, M/B)} \tag{3.3}$$

$$\text{Long-term timing } (LT) = \left(\sum_{s=0}^{t-1} (M/B)_s / t\right) * \left(\sum_{s=0}^{t-1} EF_s / t\right) = \overline{M/B} * \overline{EF} \tag{3.4}$$

where the summations are taken for each firm-year observation over the study period (1996-2006). In the spirit of Baker and Wurgler (2002), Kayhan and Titman (2007) construct a timing measure (equation 3.2) and yearly timing measure (equation 3.3) by disentangling the relationship between the market-to-book ratio, with market timing and pecking order effects. The role of yearly timing measure is somewhat similar to that of Baker and Wurgler's (2002) external weighted average market-to-book ratio. The long-term timing measure captures the effects of pecking order on financing activity, rather than market timing per se. Equation (3.2), decomposes Baker and Wurgler (2002) timing measure into the covariance between financing deficit and market-to-book ratio, and the mean market-to-book ratio. Kayhan and Titman (2007) posit that the first term in their decomposition in equation (3.2), or yearly market timing scaled by average financing deficit, is superior to Baker and Wurgler's (2002) measure, since the new measure may prevent a spurious link due to correlation between the timing measure and investment opportunities by excluding the average market-to-book ratio (($\overline{M/B)}$. As such, I use the second timing measure as follows:

$$KT\_\ timing = COVEFMB_{t-1} = \frac{Cov\,(EF,\ \ M/B)}{\overline{EF}} \qquad (3.5)$$

3.4.2 Decomposing Market-to-Book ratio Based on Rhodes-Kropf, Robinson, and Viswanathan (2005)

To address the concern that the history of concurrent increases in external financing needs and the market to book ratio are possibly affected by underlying firm characteristics rather than by market timing activity, I further construct my third measure of market timing based on the Rhodes-Kropf, Robinson, and Viswanathan' (*RKRV*) (2005) market-to-book decomposition

technique. This approach addresses other potential problems, in that the market to book ratio could be affected by underlying firm characteristics rather than by market timing activity, and the possibility of concurrent increases in external funding beyond those associated with market timing. The RKRV's (2005) measure decomposes the logarithm of the market-to-book ratio into market-to-value and value-to-book components, as follows:

$$Ln(M/B_{i,t}) = m_{it} - b_{it} = m_{it} - v(\theta_{it}, \alpha_{jt}) + v(\theta_{it}, \alpha_{jt}) - v(\theta_{it}, \alpha_j) + v(\theta_{it}, \alpha_j) - b_{i,t} \quad (3.6)$$

where m and b are logarithms of the market and book value of assets, respectively, and the subscripts, i, j, and t, denote firm, sector and time, respectively. The first component in the decomposition ($m_{it} - v(\theta_{it}, \alpha_{jt})$), or firm-specific-error component (*FSE*), measures the different between the firm's market value and its fundamental value as implied by accounting multiples θ_{it}, and industry-long run multiple α_{jt}. The second component, $v(\theta_{it}, \alpha_{j,t}) - v(\theta_{it}, \alpha_j)$, or time sector error (*TSE*), is the difference between the firm's fundamental value conditioned at time t and its long run fundamental value implied by the sector multiples (α_j), which captures time-invariant sector specific valuation. The final component, $v(\theta_{it},\alpha_j) - b_{i,t}$, or long-run value (*LRV*), is the difference between the firm's long run value as implied by its long run multiples and its book value. This component is intended to capture the firm's set of investment opportunities at time *t*.

Technically, the RKRV's (2005) decomposition isolates the firm specific misvaluation from industry-wide mispricing and firm growth opportunities. As such, the firm specific-error (*FSE*) component can be used as a purer proxy to capture firm misvaluation in a market timing study. In order to capture the cumulative effects of past timing attempts due to the firm misvaluation, I also use the external weighted average firm specific-error (*FSE*), but I use the firm specific sector instead of market to book itself.

$$RKRV\_timing = \sum_{s=0}^{t-1} \frac{EF_r}{\sum_{r=0}^{t-1} EF_r} exp(FSE_s) \quad (3.7)$$

In my final market timing measure, I also include other RKRV's (2005) decomposition components as control variables in the regressions to control for spurious relation between history and capital structure due to firm characteristics and investment prospects. This is shown as follows. The external weighted sector misvaluation (*TSE*) is calculated as follows:

$$TSE=\sum_{s=0}^{t-1} \frac{EF_r}{\sum_{r=0}^{t-1} EF_r} exp(TSE_s) \qquad (3.8)$$

and the external weighted average growth opportunities (*LRV*) as follows:

$$LRV=\sum_{s=0}^{t-1} \frac{EF_r}{\sum_{r=0}^{t-1} EF_r} exp(LRV_s) \qquad (3.9)$$

I use exponential forms of *FSE, TSE,* and *LRV* instead of actual values to avoid negative values for average variables. To calculate firm fundamental value and long-run value using annual sector-average regression multiples and long-run sector average multiples (ν(*θit, αjt*), ν(*θit, αj*)), I estimate the following model (model 3 in RKRV(2005))

$$\mathbf{m}_{i,t} = \alpha_{0jt} + \alpha_{1jt}\mathbf{b}_{it} + \alpha_{2jt}\text{Ln}\,(\mathbf{NI})^{+} + \alpha_{3jt}\text{I}_{(<0)}\text{Ln}\,(\mathbf{NI})^{+}_{it} + \alpha_{4jt}\mathbf{LEV}_{it} + \varepsilon_{it}, \quad (3.10)$$

where LEV_{it} is the leverage ratio, $(\mathbf{NI})^{+}$ is the absolute value of net income and $\text{I}_{(<0)}\text{Ln}\,(\mathbf{NI})^{+}$ I is an indicator function for negative net income observations. To obtain ν($\theta it,\ \widehat{\alpha jt}$) and ν($\theta it,\ \hat{a}j$), using equation (3.10), I perform calculation for each firm as follows using fitted values from equation (3.10) above:

$$v(\mathbf{B}_{it},\mathbf{NI}_{it}, \mathbf{LEV}_{it},\hat{\alpha}_{0jt}, \hat{\alpha}_{1jt}, \hat{\alpha}_{2jt}, \hat{\alpha}_{3jt}, \hat{\alpha}_{4jt})=\hat{\alpha}_{0jt} + \hat{\alpha}_{1jt}\,\mathbf{b}_{it} + \hat{\alpha}_{2jt}\,\text{Ln}\,(\mathbf{NI})^{+} + \hat{\alpha}_{3jt}\,\text{I}_{(<0)}\text{Ln}\,(\mathbf{NI})^{+}_{it} + \hat{\alpha}_{4jt}\,\mathbf{LEV}_{it}$$

(3.11)

And to calculate the fundamental value for the firm, I first average over time the coefficients ($\hat{\alpha}_{jt}$) to obtain long-run sector multiples ($\bar{\alpha}_{j} = 1/T \sum \alpha_{jt}$ for α_k=0,1,2,3,4), and then calculate (ν(*θit, αj*) as follows:

$$v(\mathbf{B}_{it},\mathbf{NI}_{it}, \mathbf{LEV}_{it}, \bar{\alpha}_{1j}, \bar{\alpha}_{2j}, \bar{\alpha}_{3j}, \bar{\alpha}_{4j}) = \bar{\alpha}_{0j}\,\mathbf{b}_{it} + \bar{\alpha}_{1j}\,\text{b}_{it} + \bar{\alpha}_{2j}\text{Ln}\,(\mathbf{NI})^{+} + \bar{\alpha}_{3j}\text{I}_{(<0)}\text{Ln}\,(\mathbf{NI})^{+}_{it} + \bar{\alpha}_{4j}\mathbf{LEV}_{it}$$

(3.12)

3.5 Empirical Results

3.5.1 Lines of Credit and the Probability of Equity Issuance

The central issue of this study is whether lines of credit facilitate market timing and whether misvaluation is a motive for equity offerings. This section presents the results from logistic regressions that investigate whether lines of credit foster equity issuance during the periods of misevaluation. I model the likelihood of issuing equity in a given year during the sample period as a function of firms' market-to-book ratio (*MB*) in model 1 (equation 3.13A); or firm specific error (*FSE*), time series sector error (*TSE*), and long run value to book (*LRV*) in model 2 (equation 3.13A); or capital expenditures (*CAPEX*), tangible assets (*PPE*), 12-month prior cumulative market adjusted returns (*Pre_return*), profitability (*EBITDA*), lines of credit dummy variable (*Linedummy*), financing deficit (*Deficit*), leverage ratio (*Leverage*), firm size (*Size*) in model . The logistic regression specification is as follows:

$$\Pr(\textit{Equity issuance decision} = \text{Yes}) = \frac{1}{1+e^{-u}} \tag{3.13}$$

Where $u = \beta_0 + \beta_1 (Linedummy) + \beta_2 MB + \beta_3 Pre\_return + \beta_4 Leverage + \beta_5 Deficit$

$$+\beta_6 Profitability + \beta_7 Size + \beta_8 CAPEX + \varepsilon, \quad \text{(model 1)} \tag{3.13A}$$

And, $u = \beta_0 + \beta_1 (Linedummy) + \beta_2 FSE + \beta_3 TSE + \beta_4 LRV + \beta_5 Pre\_return + \beta_6 Leverage$

$$+\beta_7 Deficit + \beta_8 Profitability + \beta_9 Size + \beta_{10} CAPEX + \varepsilon, \quad \text{(model 2)} \tag{3.13B}$$

The dependent variable is a dichotomous variable (*Seodummy*) for which new equity offerings in a given year during the sample period equal 1 and zero otherwise.

Table 3.2 Logistics Regression Analysis

Logistic regression analysis of the seasoned equity offerings (SEOs) decision as a function of firm's market to book (*M/B*) ratio (model 1), firm specific error (*TSE*), Long run misvaluation (*LRV*), Time-series error (*TSE*) (model 2), lines of credit dummy, and other control variables including size, capital expenditures (*CAPEX*), financial leverage, financing deficit, tangible assets, pre-SEO market adjusted returns (*Pre_return*) over the 12 months ending immediately before the year of SEOs, profitability. Independent variables are lagged one year before the SEO year. Two marginal effects at the means (medians) are reported to the right of the estimates.

	Model (1)	**Marginal effect (%)**		**Model (2)**	**Marginal effect (%)**		**Standard Deviation**
	(1)	At the medians	At the means	(2)	At the medians	At the means	
Intercept	-3.0851***	-	-	-3.2836***	-	-	
	(-15.82)			*(-13.51)*			
LineDummy	0.2838**	1.83	2.21	0.2847**	1.95	2.09	0.4997
	(1.98)			(1.96)			
MB	0.1305***	4.31	4.61				3.0436
	(5.88)						
FSE				0.7547***	8.07	3.12	0.2794
				(6.71)			
LRV				0.7981***	7.13	5.44	0.4573
				(4.66)			
TSE				0.1616	1.90	0.51	0.2130
				(0.57)			
Pre_Return	0.3142***	4.60	4.91	0.3415***	5.59	3.99	0.7891
	(6.69)			*(4.86)*			
Leverage	0.4941		2.89	0.4445***	3.63	2.44	0.3719
	(2.96)	*2.71*		*(2.53)*			
Deficit	0.1662	1.79	1.92	0.2419	2.75	2.63	0.7361
	(0.91)			*(1.35)*			
Profitability	0.4948	2.33	2.49	0.7238	3.60	3.44	0.3211
	(1.12)			*(1.67)*			
Size	-0.0223	-1.03	-1.12	-0.0200	-1.70	-0.93	3.1665
	(-0.94)			*(-0.80)*			
CAPEX	0.3325	0.35	0.38	0.1629	0.18	0.17	0.0729
	(0.39)			*(0.18)*			

Table 3.2 presents the logistic regression results. I capture the overvaluation by using market-to book ratio (*MB*) in model 1 (Equation 3.13A) and firm specific error (*TSE*) in model 2 (Equation 3.13B). Consistent with prior literature, the coefficients on *MB*, *FSE*, *Pre_return*, *Leverage*, and *Deficit* are all positive and statistically significant at 1 percent, suggesting that firms with high market to book ratio or high level of misvaluation, high leverage ratio, high level of financing deficit, and high cumulative returns prior to SEOs are more likely to issue equity. The magnitudes and signs of the coefficients on a set of control variables in both model 2 are very similar if market-to-book ratio is replaced with the firm specific error (*FSE*) and other two components of RKRV's (2005) market-to-book decomposition (*TSE* and *LRV*).

In addition, the coefficients on line of credit dummy (0.2838, *t*-value=1.98, and 0.2847, *t*-value=1.96 for model 1 and 2, respectively) are statistically positive in both models. The positive coefficients indicate that firms with lines of credit are more likely to issue equity during the sample period. Contrary to the conventional perception that firms would draw loans from lines of credit rather than issue new equity to avoid issuing costs, the results show the market timing of equity offerings to be more prevalent in firms with lines of credit than in those without lines of credit.

Since the slope coefficients in the logistic regression model represent change in logit corresponding to a change of one unit in the independent variable, it is hard to draw practical inferences from the estimated coefficients in the model. To facilitate interpretation, I also calculate the marginal effects (marginal effects at the mean and at the median) to show the magnitude of each explanatory variable's contribution to the probability of issuing equity for the sample firms. For dummy variable, taking *Linedummy* for example, marginal effect is a measure of the instantaneous effect that a change in line of credit (from zero (no lines of credit) to one

(with lines of credit)) has on the predicted probability of issuing new equity, when the other explanatory variables are kept fixed at their sample median or mean levels. For other continuous variables, the marginal effect, taking *FSE* for example, at the medians (means) is the difference between two probabilities, given one standard deviation change in *FSE* while other variables are kept fixed at their medians (means).

I present the marginal effects (in percentage) in the columns right next to the regular logistic coefficient columns by moving the value of variable of interest from one-half standard deviation below its median (mean) to on-half standard deviation above its median (mean) while other variables are kept fixed at their medians (means). In Table 3.2, one standard deviation change in market-to-book firm specific error variable (*FSE*) increases the probability of issuing equity about 8.07 percent (at the medians). Given the standard deviation of FSE is 0.2794, firm specific misvaluation has a large impact on the decision of equity offerings. Similarly, the marginal effects of line of credit dummy (*Linedummy*) at the mean are respectively 2.21% and 2.09% for model 1 and 2, suggesting that the probability of issuing equity in a given year during the sample period is about two percent higher for firms with lines of credit. The results reveal another important determinant of equity issuance. That is, firms having lines of credit are more likely to issue equity, possibly due to market timing behavior rather than the needs for external financing. I further investigate this issue in the following sections.

3.5.2 Misvaluation, Lines of Credit, and Market Timing

I first consider the impact of market conditions and misvaluation on capital structure and how lines of credit affect their relationship. The issue of interest is whether accessing lines of credit fosters market timing behavior and is a significant factor affecting a firm's capital structure after controlling for other firm characteristics. I use Baker and Wurgler (2002) and

Kayhan and Titman's (2007) measures in my first test to examine the roles of lines of credit in facilitating market timing. Specifically, I run the following regressions (Equation 3.14) that control for other determinants of leverage and industry fixed effects.

$$ML_{i,t} = \beta_0 + \beta_1 Linedummy_{it} + \beta_2 Linedummy{*}Marketiming_{i,t} + \beta_3 Markettiming_{i,t} + \beta_4 MB_{i,t} + \beta_5 Tangibility_{i,t} + \beta_6 Profitability_{i,t} + \beta_7 Size_{i,t} + \sum \varphi Industry + \varepsilon_{i,t} \quad (3.14)$$

The dependent variable is market leverage ratio (*ML*). The explanatory variables include dummy variable for lines of credit (*Linedummy*), marketing timing variable, the interaction between the dummy variable and market timing variable (*Linedummy*Markettiming*), and other control variables widely adopted in capital structure literature. Specifically, I employ a set of control variables as proposed in Rajan and Zingales (1995). I then construct a set of control variables following Baker and Wurgler (2002) as follows. The market-to-book ratio (*MB*) is defined as total assets minus book equity plus market equity, divided by total assets. *Tangibility* is defined as net plant, property and equipment, divided by total assets. *Profitability* is defined as earnings before interest, taxes and depreciation, divided by total assets. *Size* is defined as log of net sales. Market leverage (*ML*) is book debt divided by the result of total assets minus book equity plus market equity (in percentage term). Market timing variables include Baker and Wurgler's(2002)($MBEFWA_{t-1}$) and Kayhan and Titman's (2007) ($COVEFMB_{t-1}$) measures as discussed in the previous section. I also include a set of dummy variables to control for industry effects.

Based on my hypotheses, I predict the coefficients on market timing and the interaction between market timing and lines of credit dummy variable are both negative, if the capital structures of the sample firms are affected by market timing. The coefficient on the interaction term (*Linedummy*Markettiming)* shows the impact of lines of credit on market timing, given the

firms' market timing implementation. The negative coefficient indicates that firms with lines of credit are more active in exploiting their misvaluations by issuing equity during the sample period. I also expect the coefficients on other control variables to be consistent with prior literature. For example, Frank and Goyal (2003) and Alti (2006) find the positive relation between asset tangibility, firm size, and negative relation between profitability, market-to-book and leverage.

Table 3.3 shows the results based on the estimations of equation (3.14) above. Throughout this paper, I use the modified Fama-Macbeth (1973) procedure as proposed by Petersen (2009) to estimate regression coefficients and standard errors. Specifically, I follow Fama-Macbeth (1973) procedure but correct the standard errors of the estimated coefficients for heteroskedasticity and the clustering of observation by both firm and period. As discussed in Peterson (2009), the issues of serial correlation and cross-correlation of error terms often arise in panel data sets, typically in repeated observations on the same or a substantially overlapping, set of firms over time like the one in this study. If cross sectional and time series dependence is presence in the sample, then cluster robust standard errors are well specified and more appropriate. The first two columns show the results for the pooled sample using $MBEFWA_{t-1}$ and $COVEFMB_{t-1}$ measures as the variables of interests. The coefficients on *Markettiming* and the interaction term (*Markettiming**Linedummy*) are -1.07 and -3.30 for $MBEFWA_{t-1}$ and -1.31 and -1.39 for $COVEFMB_{t-1}$, respectively. All coefficients are statistically significant at 5 percent. The results also show the economically significant impacts the timing variables. For example, an increase in two standard deviations of $MBEFWA_{t-1}$ and $COVEFMB_{t-1}$ leads to a reduction of approximately 8.6 % and 5.1 % in the average value of *ML*. the control variables all have expected signs and statistically significant at 5 percent.

Table 3.3 The Effects of Lines of Credit on Market Timing Using BW and KT Timing Measures with KZ index

The dependent variable is market leverage (*ML*), which is defined as the ratio of total liabilities to the market value of assets. The independent variables include market timing variable (Baker-Wurgler (2002) market to book external financing variable-$MBEFWA_{t-1}$ (model 1), and Kayhan-Titman (2007)-*COVEFMB* (model 2), line of credit dummy, the interaction between *BW_timing* variable and line of credit dummy, market to book, four Kaplan and Zingales' (1995) control variables (tangibility, profitability, size), and industries dummies based on Fama and French 12 industry classification. Firms are sorted into constrained and non-constrained sample groups based Kapland and Zingales' (1995) index (*KZ index*). The coefficients and *t*-values are obtained from the modified Fama-MacBeth regressions, corrected for heteroskedasticity and the clustering of observations by both firm and period.

Model	**(1) Pooled sample**		**(2) Non-constrained (Based on KZ index)**		**(3) Constrained (Based on KZ index)**	
	BW_Timing	KT_Timing	BW_Timing	KT_Timing	BW_Timing	KT_Timing
MarketTiming	-1.8740***	-0.8166***	-0.9868***	-0.4886**	-4.3773***	-0.9927
	(-3.36)	*(-2.69)*	*(-5.04)*	*(-2.02)*	*(-3.9268)*	*(-0.77)*
MarketTiming* LineDummy	-1.0783***	-1.3073**	-2.2826***	-1.6179***	1.7768**	0.1033
	(-3.59)	*(-1.98)*	*(-4.98)*	*(-2.88)*	*(2.58)*	*(0.06)*
LineDummy	3.3069**	1.3975*	6.7848***	2.7263***	-6.0466***	-1.768
	(2.67)	*(1.92)*	*(8.18)*	*(2.71)*	*(-3.18)*	*(-1.07)*
Market-to-book	-3.8907***	-2.3981**	-3.1522***	-1.7809***	-4.7245***	-3.5705***
	(-10.79)	*(-4.13)*	*(-4.95)*	*(-3.50)*	*(-9.82)*	*(-6.23)*
Tangibility	0.2159***	0.1051***	0.2206***	0.1191***	0.0433**	0.0559
	(8.52)	*(3.82)*	*(13.23)*	*(3.95)*	*(2.61)*	*(1.09)*
Profitability	-0.0938***	-0.1047***	-0.1157***	-0.0983***	-0.0532	-0.0616
	(-3.80)	*(-3.47)*	*(-5.75)*	*(-3.42)*	*(-1.11)*	*(-1.33)*
Size	0.7184**	0.3396**	0.5418	0.3211	0.4280	1.1169***
	(2.37)	*(2.06)*	*(1.47)*	*(1.48)*	*(0.87)*	*(3.53)*
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes

Next, I examine whether the effects of the lines of credit on market timing are more pronounced for unconstrained firms. Four right-most columns of Table 3.3 shows results for two

subsamples, namely unconstrained and constrained samples. I sort firms into constrained and non-constrained samples using the Kaplan and Zingales' (KZ) index of constraints. The KZ index is a linear combination of five variables: debt to total capital (positive relationship), dividends to capital (negative relationship), cash holdings to capital (negative relationship), cash flow to capital (negative relationship), and Tobin's Q (positive relationship) (Equation 3.15). More constrained firms have a higher KZ index and vice versa. More specifically, I follow Lamont et al., (2001) to construct KZ index as follows:

$$\begin{aligned} \text{KZ Index} = &-1.002 \times (\text{Cash Flows} / K) + 0.283 \times Q + 3.139 \times (\text{Debt} / \text{Total Capital}) \\ &-39.368 \times (\text{Dividends} / K) - 1.315 \times (\text{Cash} / K)^{5} \end{aligned} \tag{3.15}$$

I report coefficients of market timing and other control variable for non-constrained sample in the two columns in the middle of Table 3.3. The signs of the coefficients obtained from the unconstrained sample are similar to those of coefficients obtained from the pooled sample, suggesting the same effects of lines of credit on market timing. For example, the coefficients on timing variable ($MBEFWA_{t-1}$) and the interaction term (*MarketTiming*LineDummy*) are -0.9868 (-0.4886) and -2.2826 (-1.6179), respectively. Interestingly, I find no such pattern on coefficients of timing variables and interactional terms between timing variable and the indicator for lines of credit in the constrained sample. While the signs of coefficient on timing variables are still negative, the signs of interaction between dummy variable for lines of credit and two measures of market timing (*MarketTiming*LineDummy*) are positive and significant at 1 percent for Baker and Wurgler's

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[5] I directly use the same variable definitions from Lamont et al., (2001) to construct KZ index. Cash flow is defined as operating income plus depreciation (Compustat item 18 + item 14). Tobin's Q is defined as book assets minus book common equity minus deferred taxes plus market equity) / book assets calculated as [item 6 − item 60 − item 74 + (item 25 × item 24)] / item 6. Debt is defined as short-term plus long-term debt (item 9 + item 34). Total capital is defined as debt plus total stockholders' equity (item 9 + item 34 + item 216).

(2002) measure (*$MBEFWA_{t-1}$*) and 10 percent for Kayhan and Titman's (2007) measure (*$COVEFMB_{t-1}$*). This indicates that financially constrained firms find it difficult to employ market timing strategies even with lines of credit. The right most column of Table 3.3 offers no evidence that financial constrained firms are not able to timing the market. These results provide support for my argument that it is difficult enough for constrained firms to raise external capital, let alone time the market.

I reach similar conclusions when I use a different proxy for financial constraints. Table 3.4 also reports the results using the Altman Z-score[6] and the Ohlson O-score[7] to sort firms into the financially constrained and non-constrained samples. All coefficients for timing variables and interaction between timing variable and the indicator for lines of credit are negative and statistically significant at 5 percent for pooled sample and non-constrained sample. Similarly, the results for unconstrained sample by using different sorting criteria indicate there are no effects of lines of credit on market timing.

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[6] The Altman Z-Score is a measure of a company's health and likelihood of bankruptcy based on Altman (1968). The Z-score is constructed as follows: Z = 1.2*(WC/TA) + 1.4*(RE/TA) + 3.3*(EBITDA/TA) + 0.6*(ME/TL) + 1.0* (Sales/TA). *WC* is defined as working capital. *TA* is total assets. RE is retained earnings. *EBITDA* is earnings before interest, taxes, depreciation and amortization. ME is market equity. *TL* is total liabilities. Firms with Z-Score < 1.81 are sorted into constrained sample, while firms with Z-Score >3.0 are sorted into non-constrained sample.

[7] I follow Ohlson (1980) to construct O-Score as follows:
O-Score= -1.32-0.407*Size+6.03*TLTA-1.432*WCTA+0.076*CLCA-1.72*OENEG-2.37*NITA-1.83*FFOLT +0.285*INTWO-0.521*CHIN. Size or market assets are defined as market total liabilities plus market equity (price times shares outstanding) divided by consumer price index (CPI). *TLTA* is defineds as the book value of debt divided by market assets.*WCTA* is working capital divided by market assets. *CLCA* is current liability divided by current assets. *ONENEG* is one if total liabilities exeeds total assets and is zero otherwise. *NITA* is net income divided by assets. *FFOLT* is the funds from operations divided by liability. *INTWO* is equal to one if net income is negative for the last two years and zero otherwise. *CHIN* is defined as ($NI-NI_{t-1}$)/(absolute(NI)+absolute (NI_{t-1}), where NI_i is net income for the most recent quarter.

Table 3.4 The Effects of Lines of Credit on Market Timing Using BW and KT Timing Measures with Atman Z-Score and Ohlson's O-Score

Firms are sorted into constrained and non-constrained groups based on Atman's Z-score and Ohlson's (1980) O-score. The dependent variable is market leverage (*ML*), which is defined as the ratio of total liabilities to the market value of assets. The independent variables include $MBEFWA_{t-1}$ and $COVEFMB_{t-1}$, line of credit dummy, the interaction between timing variable and line of credit dummy, market to book, four Kaplan and Zingales' (1995) control variables (tangibility, profitability, size), and industries dummies based on Fama and French 12 industry classification. The independent variables, except for market to book ratio, are scaled by total assets and lagged one period relative to the dependent variables. The coefficients and *t*-values are obtained from the modified Fama-MacBeth regressions, corrected for heteroskedasticity and the clustering of observations by both firms and period.

Model	**Non-constrained Altman's Z-score**		**Constrained Altman's Z-score**		**Non-constrained Ohlson's O-score**		**Constrained Ohlson's O-score**	
	BW_Timing	KT_Timing	BW_Timing	KT_Timing	BW_Timing	KT_Timing	BW_Timing	KT_Timing
MarketTiming	-0.7123***	-0.7937**	-3.1596***	-1.2778	-0.4376**	-0.1356	-3.1657***	-2.6272**
	(-6.48)	*(-2.41)*	*(-7.82)*	*(-1.08)*	*(-2.36)*	*(-0.38))*	*(-5.03)*	*(-2.49)*
MarketTiming* LineDummy	-2.7155***	-1.0090**	0.5634	1.2080	-2.5620***	-2.4263***	0.7107	1.4411
	(-6.91)	*(-2.15)*	*(1.64)*	*(0.82)*	*(-5.21)*	*(-2.25)*	*(1.44)*	*(0.88)*
LineDummy	12.0713***	2.6014**	-5.1107***	-3.9051**	11.6545***	4.8870***	-1.6256	0.2638
	(4.57)	*(2.45)*	*(-2.75)*	*(-2.87)*	*(4.49)*	*(3.19)*	*(-0.86)*	*(0.11)*
Market-to-book	-3.0974***	-2.4440***	-2.6637**	-3.0878***	-3.7540***	-2.9197***	-3.2564***	-3.4302***
	(-11.20)	*(-4.27)*	*(-2.56)*	*(-3.17)*	*(-10.43)*	*(-4.85)*	*(-5.23)*	*(-6.25)*
Tangibility	0.0221***	0.0181**	0.0958**	0.0783**	0.1141***	0.0776***	0.1507***	0.1277***
	(2.99)	*(2.19)*	*(2.97)*	*(2.48)*	*(5.60)*	*(4.04)*	*(12.90)*	*(4.02)*
Profitability	-0.1412***	-0.1000***	0.0466	0.0423	-0.0920***	-0.0956***	-0.0093	-0.0033
	(-5.70)	*(-3.65)*	*(0.92)*	*(0.93)*	*(-3.81)*	*(-2.88)*	*(-0.35)*	*(-0.11)*
Size	2.1455***	1.1861***	0.7041	0.6227	1.6616**	0.8688**	0.6038	-0.0514
	(7.03)	*(3.50)*	*(1.44)*	*(1.54)*	*(2.19)*	*(2.26)*	*(0.55)*	*(-0.07)*
Adj. R^2	0.4645	0.4982	0.3491	0.3279	0.4100	0.3901	0.4784	0.4659

Table 3.5 The Effects of Lines of Credit on Market Timing: Using RKRV's (2005) Timing Measure with KZ index

The dependent variable is market leverage (*ML)*, which is defined as the ratio of total liabilities to the market value of assets. The independent variables include market timing variable (Rhodes-Kropf, Robinson, and Viswanathan's (2005) firm specific error (*FSE*), which capture stock misvaluation), line of credit dummy, the interaction between *FSE* timing variable and line of credit dummy, market to book, Kaplan and Zingales' (1995) control variables (tangibility, profitability, size), and industries dummies based on Fama and French 12 industry classification. The independent variables, except for market to book ratio, are scaled by total assets and lagged one period relative to the dependent variables. The coefficients and *t*-values are obtained from the modified Fama-MacBeth regressions, corrected for heteroskedasticity and the clustering of observations by both firm and period.

Model	**Pooled sample**	**Non-Constrained** (Based on KZ index)	**Constrained** (Based on KZ index)
MarketTiming ($EFWA\_FSE_{t-1}$)	-2.6166**	-2.6496**	8.3495**
	(-2.22)	*(2.32)*	*(2.48)*
MarketTiming*LineDummy	-3.8939***	-5.9721***	0.5787
	(-3.34)	*(-4.43)*	*(0.17)*
LineDummy	1.5103	2.8692***	-0.0035
	*(1.97)**	*(4.22)*	*(-0.00)*
Market-to-book (MB_t)	-1.5887***	-1.7620***	-3.1689***
	(-6.80)	*(-6.14)*	*(-5.85)*
Tangibility (PPE_{t-1})	0.3078***	0.1645***	0.0204
	(30.12)	*(11.23)*	*(0.57)*
Profitability ($EBITDA_{t-1}$)	-0.1426***	-0.1656***	-0.1477***
	(17.09)	*(19.86)*	*(-3.44)*
$Size_{t-1}$ (*Ln(sale)*)	0.5676	0.4882	-0.8939
	(-1.58)	*(-0.90)*	*(-1.04)*
TSE (Time Series Sector Error)	-8.3154	-6.8834	-31.795
	(-0.54)	*(-0.49)*	*(-1.10)*
LRV(Long-run Value to Book)	-51.037***	-45.935	-47.679***
	(-27.02)	*(-27.60)*	*(-9.47)*
Industry Dummy	Yes	Yes	Yes
Adj. R^2	0.5407	0.5403	0.5650

The coefficients on interaction terms between timing and dummy for lines of credit variables are positive and not statistically significant. Regardless of sorting criteria there is no support for the market timing.

Thus far, I demonstrate an empirical relation regarding the role of lines of credit in fostering market timing. I have also provided several analyses of corroborating evidence in support of the hypothesis that financially constrained firms are not able to time the market even when they have access to lines of credit, or committed loans. To shed more light on the roles of credit lines in facilitating market timing, I expand my analyses by using the third market timing measure, which is based on RKRV's (2005) decomposition of market-to-book.

Table 3.5 reports the results of the regressions with external finance weighted average firm specific error (*FSE*) as my timing measure and external finance weighted average time series sector (*TSE*), external finance weighted average long-run value to book (*LRV*) as two additional explanatory variables. I use KZ index to sort firms into constrained and non-constrained samples. As usual, I am interested in coefficients on timing variable and the interaction term between the timing variable and the dummy for credit lines. Consistent with prior results, coefficients on timing variables and the interaction terms are both negative and statistically significant at 1 percent for the pooled sample and the non-constrained sample. For the constrained sample, I do not find any evidence of market timing since the coefficient estimate of timing variable (*EFWA_FSE*) and the interaction term (*Markettiming*Linedummy*) are 8.3495 (*t*-statistic=2.48) and 0.578 (*t*-statistic=0.17), respectively. The positive signs of both coefficients indicate that constrained firms possibly have no scope for market timing, given their limited flexibility in raising external financing. Another explanation can be found in the survey of Campello et al. (2011). That is, financially constrained firms with low internal resources are

more likely to preemptively draw on their lines of credit because they are most likely to be rationed when their lenders have their own problems. Consequently, constrained firms exhaust their credit lines faster than non-constrained firms. If so, constrained firms are not able to engage in market timing by temporarily draw down the funds from credit lines. In other words, constrained firms that either preemptively draw on lines of credit to avoid credit rationing or exhaust their credit lines due to liquidity shocks are not able to time their equity even they can identify "windows of opportunity".

Table 3.6 reports the regression results using *EFWA_FSE* as timing variable and Altman's Z-Score and Ohlson's O-Score to sort firms into two subsamples, constrained and non-constrained. Again, I observe that the estimated coefficients of the variables of interest are indeed similar to those in Table 3.5. Although the coefficient on market timing variable for the non-constrained sample using O-score sorting criteria market is negative while the coefficient on the interaction terms between market timing and the dummy for credit lines is positive. This suggests that the presence of credit lines does not affect market timing for constrained firms.

Overall, results reported across all tables using different measures for market timing and financial constraints provide evidence of market timing such that firms issue equity when equity prices are high and issue debt when equity prices are low. In addition, market timing activity could be amplified with the presence of lines of credit. I find that accessing to credit lines allows non-constrained firms to actively engage in market timing, thus possibly creating more value to such firms. However, I could not found any effects of lines of credit on market timing in the constrained sample. The findings are robust to different sorting criteria including KZ-index, Altman's Z-Score, and Ohlson's O-Score.

Table 3.6 The Effects of Lines of Credit on Market Timing: Using RKRV Timing Measure with Altman Z-score and Ohlson O-score.

The dependent variable is market leverage (*ML*), which is defined as the ratio of total liabilities to the market value of assets. The independent variables include market timing variable (Rhodes-Kropf, Robinson, and Viswanathan's (2005) firm specific error (*FSE*), which capture stock misvaluation), line of credit dummy, the interaction between *FSE* timing variable and line of credit dummy, market to book, Kaplan and Zingales' (1995) control variables (tangibility, profitability, size), and industries dummies based on Fama and French 12 industry classification. The coefficients and *t*-values are obtained from the modified Fama-MacBeth (1973) regressions, corrected for heteroskedasticity and the clustering of observations by both firm and period.

		Altman's Z-score		**Ohlson O-score**	
	Pooled Sample	Non-constrained	Constrained Sample	Non-constrained	Constrained Sample
MarketTiming	-2.6166**	-1.4637**	4.4879	-3.983**	-7.1730
	(-2.22)	*(-2.33)*	*(0.95)*	*(2.70)*	*(-3.51)*
MarketTiming*LineDummy	-3.8939***	-10.093***	-1.2127	-10.190***	11.6984***
	(-3.34)	*(-4.69)*	*(-0.23)*	*(-8.19)*	*(3.41)*
LineDummy	1.5103*	5.6811***	-2.0351	7.0504***	-3.2083*
	(1.97)	*(3.11)*	*(-1.07)*	*(12.43)*	*(-2.02)*
Market-to-book	-1.5887***	-2.0683***	-2.8840*	-2.6028***	-2.1487**
	(-6.80)	*(-40.42)*	*(-2.25)*	*(-18.21)*	*(2.68)*
Tangibility	0.3078***	0.0326*	0.0737*	0.0924**	0.1550***
	(30.12)	*(2.05)*	*(2.01)*	*(2.76)*	*(7.35)*
Profitability	-0.1426***	-0.1357***	-0.0605	-0.1180***	-0.0732**
	(17.09)	*(-7.28)*	*(-1.75)*	*(-3.35)*	*(-2.98)*
Sector Error	0.5676	-0.2032	-15.924	0.6806	-25.188
	(-1.58)	*(-0.01)*	*(-0.69)*	*(0.06)*	*(-1.28)*
Long-run Misvaluation	-8.3154	-32.765***	-41.627***	-33.396***	-45.265***
	(-0.54)	*(-11.43)*	*(8.28)*	*(-13.25)*	*(-7.76)*
Size	-51.037***	0.7301*	-0.0121	-0.0082	-1.5910
	(-27.012)	*(1.93)*	*(-0.02)*	*(-0.01)*	*(-1.22)*

3.5.3 Lines of Credit and the Underpricing of Seasoned Equity Offerings

Several studies have documented significant undepricing in seasoned equity offerings (e.g., Corwin (2003, Mola and Loughan (2004)). SEO underpricing occurs when the offer price is lower than the closing price on the day prior to the offer date. Scholars have developed several theories to explain the underpricing of SEOs. For example, information asymmetry theory (e.g., Myers and Majluf (1984)) explains that managers are tempted to mislead outside investors by issuing equity when their stocks are overvalued. Anticipating such a tactic, outside investors will discount the prices they are willing to pay for the firms' new shares. Thus, higher level of information asymmetry should lead to higher the level of SEO underpricing (discount). Another explanation is that underwriters have an incentive to leave money on the table for outside investors during SEOs in order to get the job done, thus enjoying high reputation and recognition from customers. Prior empirical studies document that the major determinants of SEO underpricing include the level of information asymmetry, the level of uncertainty about firm value, underwriter reputation, relative offer size, and conventional underwriter pricing practices (Altinkilic and Hansen, 2002; Corwin 2003).

If lines of credit help firms to delay their equity offerings until suitable market conditions appear, they would help firms to push up their offer prices during "windows of opportunity" periods. As such, firms may experience a lower degree of underpricing through SEO episodes. In this section I analyze the effects of lines of credit on SEO underpricing. My hypothesis is that firms accessing lines of credit are more likely to experience a lower degree of SEO underpricing. To test this hypothesis, I use the following regression specification (Equation 3.16):

$$Underpricing = \beta_0 + \beta_1 Linedummy + \beta_2 Precar + \beta_3 IPOUnderpricing + \beta_4 Volatility + \beta_5 Offersize + \beta_6 Rank + \beta_7 Tick + \beta_8 Size + \beta_9 NASDAQ + \varepsilon, \quad (3.16)$$

The dependent variable is *Underpricing*, defined as the closing price on the offer day minus the offer price, divided by the offer price. I also use the second proxy for *Underpricing*, namely *Discount* for my regressions. *Discount* is the closing price on the day prior to the offer minus the offer price, divided by the closing price on the day prior to the offer. Along with my variable of interest, *Linedummy*, I also include a set of explanatory variables that are widely adopted in the literature. First, *Volatility* variable, proxied for stock price uncertainty, is defined as the standard deviation of stock returns over the period of 30 trading days ending 10 days prior to the offer date. I expect a positive coefficient on *Volatility* since Corwin (2003) finds higher return volatility is associated with higher levels of underpricing. Second, *PreCar* variable, proxied for pre-offer price run up, is defined as the cumulative adjusted returns over the period of 5 trading days prior to the offer. I expect a positive coefficient on *PreCar* since the literature on SEO underpricing (e.g., Loughran and Ritter (2002)) has documented that the equity issuers are more tolerant of excessive underpricing if they simultaneously learn about a post market valuation that is higher than what they expected. Therefore, issuers who see greater recent increases in their stock price have the edge over their contracted underwriters in setting the offer prices. This also implies that pre-offer abnormal stock returns are positively related to the magnitude of the SEO underpricing.

In addition, I follow Corwin (2003) to control for the effects of price pressure with the variable *Offersize*, calculated as shares offered divided by the total number of shares outstanding prior to the offer. I also include *Tick*, which is a dummy variable equals to one if the decimal portion of the closing price on the day prior to the offer is less than $0.25, and zero otherwise, to reflect the effects of rounded prices on SEO underpricing. Other control variables include *IPOUnderpricing*, measured as the average underprcing across all IPOs during the same month

as the SEO, and NASDAQ dummy variable that equals one if the issuers are listed on NASDAQ, and zero if on NYSE or AMEX at the time of offer. Finally, I use *Rank* to control for quality of underwriters. I obtain information on underwriters' ranking for the lead underwriter for each SEO in the sample from Jay Ritter's website (http://bear.warrington.ufl.edu/ritter/).

Table 3.7 reports the results from univariate and multivariate tests of the effects of lines of credit on SEO undepricing. Panel A table 3.7 shows that both mean and median levels of issuers with lines of credit are much smaller than those of issuers without lines of credit. Specifically, the mean *Underpricing (Discount)* of issuers without lines of credit are 0.0435 (0.044), while the mean *Underpricing (Discount)* of issuers with lines of credit are 0.029 (0.0288). The difference between the means of two samples is statistically significant at 1 percent. With regard to multivariate analysis, Table 3.7 panel B provides strong evidence to support my hypothesis. The coefficients on *Linedummy*, -0.0072 (*t*=1.98) for *Underpricing* and -0.0069 (*t*-statistics=2.97) of *Discount*, are negative and statistically significant at 5 percent, suggesting that lines of credit allow issuers to time their offerings to get more favorable offer prices.

Other control variables are consistent with prior studies. For example, the signs of *PreCar*, *Volatility, and Offersize* are all positive and statistically significant. SEO underpricing increases with volatility of stock returns prior to SEOs, relative offer size, and pre-offer abnormal returns. The negative coefficients on *Rank* suggest that SEO underpricing decreases with underwriters' reputation. Also, issuers listed on NASDAD stock exchange experience higher levels of SEO underpricing.

Table 3.7 The Effects of Lines of Credit on SEO Underpricing

Panel A presents *t*-test analysis of the effects of line of credit on SEO underpricing. Panel B lists coefficients (*t*-values) from OLS regressions of SEO underpricing (SEO discount) on line of credit dummy and a set of control variables. *P*-values are based on White's (1980) heteroskedasticity consistent standard errors. Note: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A: the t-Test Analysis		
	Mean (SEO Underpricing)	Mean (SEO Discount)
Group 1 (147 firms without lines of credit)	0.0435	0.0441
Group 2 (816 firms with lines of credit)	0.0291	0.0288
Difference (Group 2-Group 1)	-0.0144***	-0.0153***
t-value	*(3.40)*	*(4.76)*
Panel B: Multivariate Analysis		
Model	**SEO Underpricing**	**SEO Discount**
Intercept	0.0442***	0.0568***
	(4.10)	*(7.51)*
LineDummy	-0.0072**	-0.0069***
	(-1.98)	*(-2.67)*
PreCar	0.2459***	0.0986***
	(19.55)	*(10.96)*
IPOUnderpricing	-0.0121**	-0.0132
	(-2.17)	*(-3.27)*
Rank	-0.0037***	-0.0052***
	(-3.34)	*(-6.40)*
Volatility	0.7023***	0.3791***
	(7.90)	*(5.90)*
Offersize	0.0306***	0.0141***
	(3.73)	*(2.97)*
Tick	-00056**	0.0005
	(-2.02)	*(0.26)*
Nasdaq	0.005**	0.0011
	(1.96)	*(0.44)*
Adj. R^2	0.3427	0.2511

3.6 Robustness

To examine the evolution of the capital structure over time, I conduct robustness tests by creating propensity matched pair samples[8]. The matching of firms with credit lines with firms without credit lines provides a testable sample that mitigates the bias in my previous tests due to sample selection bias. Specifically, I match 75 randomly selected firms in the non-credit line sample with 75 firms in the credit line sample on the basis of their propensity score in their IPO years, which is a measure of the firm's propensity to have a line of credit based on the firm's characteristics (*ROA, Size, Z-Score, and Leverage*). I simply choose a single, "nearest neighbor" match without replacement. I conduct matched-pairs *t*-tests to examine whether firms with lines of credit have more net equity and debt issues over years than those without lines of credit. Also, I investigate whether firms without lines of credit are more likely to experience a lower degree of SEO underpricing for their equity offerings. To save space, I do not report the results here. The results based on matched sample analyses confirm my previous findings. That is, firms accessing lines of credit are more likely to engage in market timing (more net debt and equity issues) and experience a lower degree of SEO underpricing.

3.7 Conclusion

This study examines the impact of lines of credit on market timing. I argue that a firm with an accession to a line of credit is more likely to actively time the equity market since lines of credit, though not perfect substitutes for cash holdings in liquidity management, allow firms to delay offerings until market conditions become favorable, thereby creating more value for current shareholders. I test this hypothesis by using both logistic and OLS regressions with modified Fama-MacBeth (1973) estimation procedures, corrected for heteroskedasticity and

[8] The seminal paper in the matching literature is Rosenbaum and Rubin (1983).

clustering of observations by both firms and time periods. I find strong support for my prediction that lines of credit foster market timing, especially for non-constrained firms. In contrast, I do not find support for my argument in the financially constrained sample firms.

I also examine whether lines of credit help firms to lower their level of SEO underpricing when they engage in equity offerings. I expect issuing firms with lines of credit to have better offer prices if lines of credit allow them to time the markets. My findings again support the argument that lines of credit lines allow firms to engage in market timing, with less associated SEO underpricing, thereby creating more value to the issuing firms. Overall, these findings shed new light on how lines of credit can create more value to a firm through the market timing channel.

Chapter 4

The Effects of Covenant Violations on the Implied Cost of Equity Capital and the Underpricing of Seasoned Equity Offerings

4.1 Introduction

A growing body of literature on the effects of covenant violation shows that creditors play a significant role in the corporate governance of firms in technical defaults. For example, prior studies (Chen and Wei, 1993; Sweeney, 1994; Robert and Sufi, 2009, Nini, Smith, and Sufi, 2012) provide evidence that violating covenants is costly for the borrowing firm because the borrowing firm is more likely to pay higher costs for their subsequent loans and to experience other costly concessions such as under investment costs resulting from future capital expenditure restrictions set forth in the amended loan contracts after re-negotiations. For instance, Nini, Smith, and Sufi (2012) find that investment spending is significantly reduced after covenant violations and Robert and Sufi (2000) find that covenant violations are associated with a lower level of debt issuance and lower financial leverage. In addition, violating firms are more likely to have poor credit ratings, thus resulting in a lower borrowing capacity and higher financing costs. Nini, Smith, and Sufi (2009) also show that while covenant violations rarely lead to bankruptcy or liquidation, they generally lead to amended agreements with higher interest rates, shorter maturity, and less funding compared with agreements prior to violations. Also, amended agreements are likely to contain more restrictions on cash management and to require collateral.

Prior empirical studies have mainly focused on the costs of covenant violations regarding agency cost of debts such as underinvestment costs and higher cost of debts (e.g., Dichev and Skinner (2002); Beneish and Press (1993)). Although some studies generally show the effects of

violations on the costs of borrowing in terms of higher interest rates and lower borrowing capacity, they do not quantify the effects of covenant violations on the cost of equity, especially the direct costs of equity, or SEO underpricing, through post violation SEO episodes of violating firms. This paper contributes to the current literature by extending earlier studies that investigate the direct impact of covenant violation on firm value. More specifically, this study examines and quantifies the effects of covenant violations on the implied cost of equity capital based on increasing perceived risks. It is widely known that the cost of debt is positively correlated with the cost of equity if firms become riskier after covenant violations. Investors in higher risk firms would require higher required returns, so the cost of equity goes up when firm risk increases. Therefore, in this study I investigate the effects of covenant violations on the cost of equity after controlling for the levels of financial risks.

One might argue that an increase in the cost of equity after a covenant violation is mainly attributed to the change in operating risks due to performance deterioration prior to the violations. It should be noted, however, that violating firms are not necessarily higher operating risk firms than non-violating ones since violations depend not only on performance deterioration but also on the covenants' strictness. Borrowers that expect to stay in covenant compliance by having a better future performance or having fewer risk shifting opportunities may prefer contracts that provide lenders with strong control rights via tight covenants in exchange for more favorable loan terms (Garleanu and Zwiebel, 2009). Hence, firms are more likely to violate covenants if they chose on an ex-ante basis tight covenants for more favorable loan terms even when their performance is generally better than average. For example, Demiroglu and James (2012) show that despite the average improvements both in covenant variables and other performance measures, firms with tight covenants are more likely to violate their covenants.

The increase in the cost of equity capital following a violation could be caused by higher perceived risk resulting from market reactions to the violation as well as by higher financial risk outcomes materially resulting from higher leverage/higher probability of bankruptcy. To disentangle the effects of covenant violation announcements on the cost of equity capital based on the market's reactions (analysts' earnings estimate revisions) to violation announcements, I test whether the change in the implied cost of equity capital observed surrounding covenant violations is statistically significant and robust to the inclusion of control variables for a sample of violating firms by using difference-in-difference and discontinuity regression approach. Specifically, I investigate the change in the cost of equity capital due to higher perceived risk rather than the actual outcomes caused by creditor intervention by comparing the ex-ante cost of equity implied in analysis earnings forecasts and stock prices before and after violations. I measure the post violation implied cost of equity for violating firms based on stock analyst revisions after the violation announcements.

Using a sample of 1,028 first-time covenant violations from 1996-2011 of the public firms in the United States, I find that covenant violators on average experiences a 8.48 percent increase in the implied cost of equity capital. I perform several robustness tests using four common models in estimating the cost of equity capital implied by analysts' earnings forecasts, stock prices, and accounting data. I also examine the effects of violation announcements and quantify the change in the cost of equity given both market reactions to higher perceived risk and possible credit interventions following violations by comparing the change in cost of equity of violating firms with that of the benchmark sample firms that have the same level of financial risks (leverage) before and after the violations. To find the benchmark sample, I match violating firms to nonviolating firms based on the ex-ante likelihood of a debt covenant violation (implied

covenant violation) prior to the violation announcements using propensity score matching method. I also investigate the effect of covenant violations on SEO underpricing for a sample of SEOs conducted during three year period immediately following covenant violations, with the expectation that one penalty for violating a covenant is that subsequent SEOs suffer from greater underpricing .

The results show that on average covenant violators experience about 3.42 percent SEO underpricing for their new offerings following violations while non-violators generally experience only about 2.8 percent underpricing. The difference is statistically significant. Prior research on covenant violation has not directly measured the cost of equity capital effects. In addition, to my current knowledge, this is the first study that directly connects covenant violations with the cost of equity capital and SEO underpricing. The remainder of this chapter is organized as follows. Section 4.2 provides related literature. Section 4.3 describes the sample selection process and descriptive statistics. Section 4.4 presents four different models of the cost of equity estimation. Section 4.5 provides the empirical results and Section 4.6 concludes the chapter.

4.2 Related Literature

A debt covenant or a contract between the lender and borrower is designed to mitigate agency problems, especially those arising from conflicts between shareholders and bondholders. A typical covenant contain terms that restrict the borrowing firm from engaging value destroying or risk shifting activities. In exchange, the borrower often receives more favorable loan terms and/or more credit from the lender.

Prior literature shows that creditor influences over covenant violators include reducing investment to reduce net debt issuance and even firing underperforming CEOs (Roberts and Sufi,

2009; Nini et al., 2011; Ozelge and Saunders, 2011). If a borrowing firm breaches the loan contract or violates the covenant, the borrower technically defaults on the loan, resulting in loan recall or accelerated loan payments. Technically, the control rights are transferred to the lender upon the violation, thus leading to the intervention by the lender that significantly affects the borrowing firms' operation regarding investment and financing activities (Baird and Rawsmussen, 2006). Recently, Chava and Roberts (2008) show that technical defaults, despite the available option of renegotiation, are associated with the transfer of control rights from shareholders to lenders, which lead to a reduction in firms' capital expenditures.

Several empirical studies also show that covenant violations or technical defaults are usually triggered by deteriorating corporate conditions (Beneish and Press 1993; El-Gazzar ,1993), and that defaults translate into material costs and negative stock returns for offending firms (Beneish and Press 1993, 1995). This research contributes to the growing body of literature on the effect of covenant violations on firm behavior (e.g., Beneish and Press 1993, 1995; Dichev and Skinner 2002; Chava and Roberts 2008; Roberts and Sufi 2009).

I make the following contributions to this literature. First, I provide a different analysis of the impact of covenant violations on corporate financing behavior. More specifically, I directly quantify the effect of violations on the cost of equity capital implied by analysts' earnings forecasts revisions surrounding violations. Second, to the best of my knowledge, this is the first study on the impact of covenant violations on the underpricing of seasoned equity offerings. My results on the underpricing of seasoned equity offerings suggest that creditors also play an important role in firm's financing decisions, especially during the period immediately following covenant violations.

4.3 Sample Selection and Descriptive Statistics

To examine the effect of covenant violations on the cost of capital, I start with the sample of covenant violation provided by Nini et al. (2008), and then use a web crawler to extend their sample until the end of 2011. I update their sample using the same technique as described in their paper. Specifically, I program a web crawler that is able to search every 10-K annual filing to identify whether a firm violates a covenant by retrieving needed information based on certain phrases. This is accomplished by linking each firm year observation from our sample to its respective 10-Q or 10-K SEC filing through CIK identifier provided by both SEC-Edgar database and Compustat.

I use the program to search seven phrases in each electronic filing on SEC's Edgar database that may indicate whether a firm violates a covenant. The six phrases include "*covenant*," "*waiv*," "*viol*," "*in default*," "*modif*," and "*not in compliance*". Whenever the program finds one of the search phrases, it pulls the related information such as CIK and GVKEY from the filings and downloads the paragraph containing such phrases into an excel file for further manual check to avoid a Type I error. Type I errors occur when the search program finds the search terms in the firm year observation in question and identifies a firm as having a line of credit when in fact it has not accessed a line of credit during that year.

I create a dummy variable (*Violation*) that takes the value of 1 if a firm violates covenants in a given quarter, and zero otherwise. Using CIK identifier and links provided by SEC on its website, the text search program is able to identify 4,538 firms with at least one violation over the period of 1996-2011. I exclude financial firms from the sample and then match the sample with the Compustat/CRSP and the Institutional Broker's Estimate System (IBES) to retrieve analysts' earnings forecast, stock price, and other accounting variables to estimate the implied cost of capital. I also require that all four measures of cost of equity be available to calculate the

mean of four estimates in order to mitigate measurement errors in each model. After data loss due to missing data from merging, estimating the implied cost of equity, and constructing control variables, the actual usable size of the dataset consists of 1,028 first time violations during the sample period. Table 4.1 summarizes this sample selection process.

Table 4.1 Sample Selection Process

This table presents the sample selection process. The original sample includes 4,538 first violation during 1996-2011. I first match the initial sample to Compustat/CRSP and IBES to obtain analysts' earnings forecasts, stock prices, and accounting variables. I delete financial firms (SIC code 6000-6999). I also delete the observations with insufficient data to estimate the implied cost of equity capital based on four models. I also delete observations with missing control variables. This selection process results in a final sample including 1,028 firms.

Sample Selection Process	**Observations (N)**
Number of firms with at least one covenant violation during 2006-2011 (update Prof. Sufi's covenant violation dataset until 2011)	4,538
Match to Compustat to obtain accounting data (book value equity) and delete financial industries(SIC code 6000-6900)	3,565
Match to CRSP to obtain stock price at month (-1 and +1) before and after the violation month.	2,237
Match to IBES to obtain analyst's forecasts at the month (-1 and +1) before and after the violation month	1,375
Delete firms with missing data for regressions	374
Final Sample	1,028

For robustness tests, I also generate a random sample of 300 firms from the violating sample. I then create a matched sample of 300 firms from the non-violating sample based on the propensity score matching technique. This technique allows me to match non-violating firms on the basis of their estimated likelihood of violating covenants. I directly estimate firms' propensity to violate covenants based on covenant tightness (covenant slacks) and firm characteristics, and then I match violating firms to those firms that are not in violation of covenants based on this propensity during the same period. I follow Murfin (2012) to construct

financial statement covenant slacks. Slack is measured as the difference between the observed ratio and the minimum allowable ratio as indicated in a loan contract. I retrieve covenant information for each violating firm from DealScan database. I then merge covenant levels of each firms' loan contracts with accounting data available from Compustat using a link file provided by Michael Roberts and Sudheer Chava as used in their paper in 2008. I measure covenant slack using quarterly Compustat data for each firm with the following financial statement covenants: current ratio, interest coverage, quick ratio, and debt to EBITDA, debt to tangible net worth, tangible net worth, and net worth.

Table 4.2, Panel A presents descriptive statistics and percentile of the distribution of various financial liquidity ratios and solvency measures for firms in violation of a financial covenant, and Panel B presents these for the random sample of violating firms. I generate the random sample of 300 firms from the violating sample, and create a matched sample of 300 firms from the non-violating sample based on the propensity score matching technique. This technique allows me to match non-violating firms on the basis of their estimated likelihood of violating covenants. I directly estimate firms' propensity to violate covenant based on covenant tightness (covenant slacks) and firm characteristics, and then match violating firms to those firms that are not in violation of covenants based on this propensity during the same period. Slack is measured as the difference between the observed ratio and the minimum allowable ratio as indicated in a loan contract.

Table 4.2 Summary Statistics

Panel A shows the distribution of financial ratios for new covenant violators (4,105 firms) at the time of violation during the sample period 1996-2011. A new covenant violation is a financial covenant violation for a firm that has not experienced a financial covenant violation in the previous four quarters. I also generate a random sample of 300 firms from the violating sample. I then create a matched sample of 300 firms from the non-violating sample based on the propensity score matching technique. This technique allows me to match non-violating firms on the basis of their estimated likelihood of violating covenants. I directly estimate firms' propensity to violate covenant based on covenant tightness (covenant slacks) and firm characteristics, and then I match violating firms to those firms that are not in violation of covenants based on this propensity during the same period. Slack is measured as the difference between the observed ratio and the minimum allowable ratio as indicated in a loan contract.

Panel A: Distribution of Variables for Final Sample

Ratios	10%	25%	50%	75%	90%
Total Assets (M$)	25	54	148	520	2100
Current Ratio	0.782	1.231	1.846	2.521	2.356
Net Worth to Assets	0.086	0.378	0.487	0.675	0.853
Sales/ Average Assets	0.445	0.768	1.265	1.748	2.415
Operating Cost/Average Assets	0.375	0.0678	1.105	1.534	2.248
Leverage ratio	0.031	0.175	0.314	0.472	0.648
Current ratio	0.734	1.124	1.648	2.546	3.768
Market to Book ratio	0.846	0.984	1.245	1.821	2.605
Payout Yield	0.001	0.007	0.024	0.065	0.176

Panel B: Distribution of Variables for Random Sample (300 firms)

Ratios	10%	25%	50%	75%	90%
Total Assets (M$)	25	54	148	520	2100
Current Ratio	0.423	1.033	1.745	2.214	2.524
Net Worth to Assets	0.064	0.478	0.652	0.875	1.247
Sales/ Average Assets	0.647	1.284	1.967	2.382	2.917
Operating Cost/Average Assets	0.275	0.0583	1.442	1.932	2.784
Leverage ratio	0.056	0.235	0.618	0.437	0.588
Current ratio	1.134	1.524	1.948	2.446	3.368
Market to Book ratio	0.943	1.284	1.548	2.243	2.908
Payout Yield	0.001	0.006	0.064	0.085	0.216

4.4 Models for Estimating Implied Cost of Equity Capital

I use analyst forecast revisions following a covenant violation to measure the effect of the violation on expected future earnings. Using a valuation model to estimate the implied cost equity based on forecast earnings and realized stock prices, I can empirically estimate the change in the firm's cost of equity following a covenant violation, and investigate whether the perceived risks of the violating firms is affected by the violation. It is expected that analysts would react to the violation announcements by updating their earnings forecasts based on prior accounting measures. As a result, covenant violations often lead to downward revisions of expected earnings because violations affect the default risk of earnings, thereby affecting earnings forecasts.

To answer the question regarding how much (if any) of the analyst earnings forecast revisions driven by covenant violations are attributable to changes in the cost of equity (internal rate or returns) that investors assign to future cash flows, I estimate the implied cost of equity capital using current stock prices and published forecasts of future earnings expectation from IBES database as inputs to the valuation models (see equation (4.1), (4.2), and (4.3)). Figure 1 shows the timeline of earnings forecasts for estimating the implied cost of equity.

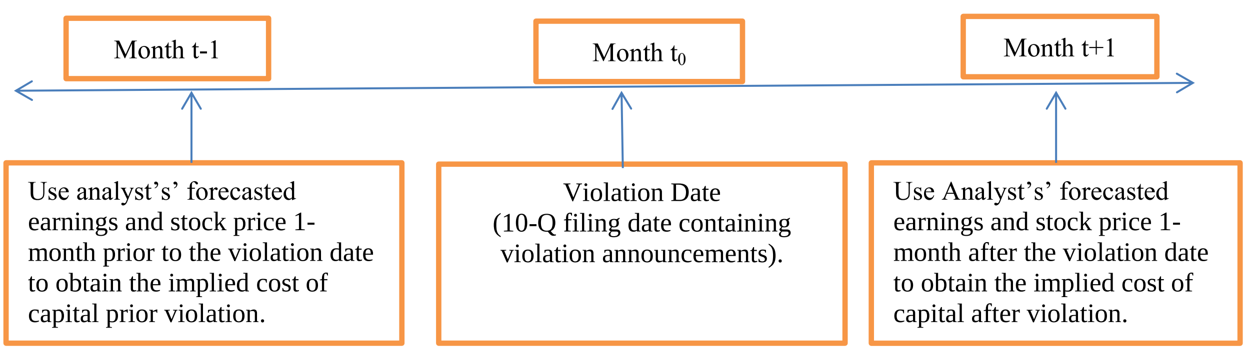

Figure 1 Timeline of Earnings Forecasts for Estimating the Implied Cost of Equity .
This figure illustrates the timeline of the earnings forecasts and the implied cost of equity capital estimation. I obtain the model-based earnings forecasts and stock prices for one month before and one month after the violations to calculate the change in implied cost of equity capital for violating firms in the sample.

Specifically, I use the models developed by Gebhardt, Lee, and Swaminathan (2001) based on Ohlson's (1995) residual income valuation model, and two others based on Ohlson and Juettner-Nauroth's (2001) abnormal earnings growth models developed by Gode and Mohanram (2002) and Easton and Monahan (2003). Since there is little consensus in the literature based on which models perform best, I follow (Hail and Leuz (2006) in using the mean (median) of the estimates from the fours model in estimating the cost of capital for my sample firms. First, the model based on Gebhardt et al. (2001) is as follows (equation 4.1):

$$P_t = B_t + \frac{FROE_{t+1} - r_e}{(1 + r_e)} B_t + \frac{FROE_{t+2} - r_e}{(1 + r_e)^2} B_{t+1} + TV \qquad (4.1)$$

Where B_t=Book value at time t,

$FROE_{t+i}$=forecasted ROE for period$t + i$,. For the first three years, I compute this variable as $FEPS_{t+1}$ /B_{t+i-1}, where $FEPS_{t+i}$ is the I/B/E/S mean forecasted EPS for year $t + i$ and B_{t+i-1} is the book value per share for year t+i-1. Beyond the third year, I use forecasted FROE using a linear interpolation to the industry median ROE. I classify firms into Fama and French's (1997) industries.

The future book value is estimated by assuming the clean surplus relation as follows: $B_{t+i} = B_{t+i-1} + FEPS_{t+i} - FDPS_{t+i}$, where FDPS is the forecasted dividend per share for year $t + i$, estimated using the current dividend payout ratio (k) multiply EPS_{t+i} (payout).

Second, the Gode and Mohanram's (2001) valuation model is as follows (equation 4.2):

$$P_t = \frac{FROE_{t+1}}{r_e} + \frac{FROE_{t+2} + r_e DVI1 \ - (1 - r_e) FROE_{t+1}}{r_e(r_e - g)} \qquad (4.2)$$

Where $FROE_{t+1}\ and\ FROE_{t+2}$ represent analyst forecasts of one year and two year ahead earnings per share taken from I/B/E/S, and DIV1 represents actual dividends per share. Growth rate (g) is set equal to risk free interest rate.

Third, I estimate the model developed by Easton and Monahan (2003) which assume no growth in abnormal earnings beyond period two as follows (equation 4.3):

$$P_t = \frac{FROE_{t+1}}{r_e} + \frac{FROE_{t+2} + r_e DVI1 + FROE_{t+2}}{(r_e + 1)^2 - 1} \qquad (4.3)$$

The dividend payout ratio is calculated by dividing dividends by earnings. I assume earnings account for 6 percent for firms with negative earnings to obtain the payout ratio.

Finally, I use the modified PEG ratio model by Easton (2004) to estimate implied cost of equity by using a numerical approximation program to solve for r_e that equates the right hand and left hand sides of the following equation with a difference of \$0.001. This model requires that $E_t(EPS) \geq E_t(EPS_{t+1})$.

$$P_t = \frac{E_t(EPS_{t+1})}{r_e} + \frac{E_t(EPS_{t+1})E_t[g_{st} - r_e(1 - payout)]}{(r_e)^2} \qquad (4.4)$$

4.5 Empirical Results

4.5.1 Impact of Covenants Violation on Implied Cost of Equity Capital

Table 4.3 and 4.4 compares the levels of implied cost of equity capital for the firms in violation of covenants based on analysts' earnings forecasts one-month before and one month after the violations as shown in the Figure 1. I estimate the cost of equity capital that is implied in analysts' earnings forecasts and current stock prices based on four models presented in Section 4.4. All continuous variables for cost of equity estimation and regression analysis are winsorized at the 1st and 99th percentiles, respectively. Table 4.3 shows the change in the implied cost of equity capital by industry over the sample period. Generally, the implied cost of equity capital increase significantly after covenant violations for firms across almost all industries.

Table 4.3 Change in the Mean of Implied Cost of Equity

This table shows the change in the implied cost of equity capital following covenant violations by industry over the sample period 1996-2011 estimated from four models introduced by Gebhardt, Lee, and Swaminathan (2001), Gode and Mohanram (2003), Easton and Monahan(2003), and Easton (2004). I obtain the model-based earnings forecasts and stock prices for one month before and one month after the violations to calculate the change in implied cost of equity capital for violating firms in the sample. I use *t*-tests to compare the means of two groups.

No	**Fama-French 48 Industry Classification**	**Before %**	**After (%)**	**Difference**	***T*-test *p*_value**
1	Agriculture	12.17	13.05	0.88	p<0.01
2	Food Products	9.43	9.95	0.52	p<0.01
3	Candy & Soda;	11.64	11.91	0.27	p<0.01
4	Recreation	10.23	10.39	0.16	p<0.00
5	Entertainment;	9.28	11.30	2.02	p<0.01
6	Printing and Publishing	12.51	13.60	1.09	p<0.01
7	Consumer Goods	9.96	11.86	1.9	p<0.01
8	Apparel	9.61	10.26	0.65	p<0.01
9	Healthcare	9.73	10.16	0.43	p>0.05
10	Medical Equipment	7.81	8.23	0.42	p>0.10
11	Pharmaceutical Products	8.84	8.40	-0.44	p>0.10
12	Chemicals	9.35	10.98	1.63	p<0.01
13	Rubber and Plastic Products	11.79	11.03	-0.76	p>0.10
14	Textiles	14.93	14.71	-0.22	p>0.10
15	Construction Materials	9.80	10.50	0.7	p<0.01
16	Construction	11.93	12.78	0.85	p<0.01
17	Steel Works Etc	11.32	9.79	-1.53	p<0.01
18	Fabricated Products	10.74	10.21	-0.53	p>0.05
19	Machinery	9.67	9.79	0.12	p<0.01
20	Electrical Equipment	9.15	9.74	0.59	p<0.01
21	Automobiles and Trucks	11.65	12.80	1.15	p<0.01
22	Aircraft	8.45	8.55	0.1	p>0.05
23	Shipbuilding, Railroad Equipment	10.31	11.30	0.99	p<0.01
24	Defense	7.78	12.82	5.04	p<0.01
25	Metallic and Industrial Metal Mining	7.61	7.97	0.36	p<0.01
26	Coal	13.22	12.95	-0.27	p>0.10
28	Petroleum and Natural Gas	9.14	9.46	0.32	p<0.01
29	Communication	10.23	10.89	0.66	p<0.01
30	Personal Services	8.53	9.85	1.32	p<0.01
31	Business Services	9.05	11.94	2.89	p<0.01
32	Computers	9.69	10.36	0.67	p<0.10
33	Electronic Equipment	8.76	9.14	0.38	p<0.01
34	Measuring and Control Equipment	7.13	6.95	-0.18	p<0.01
35	Business Supplies	10.26	10.86	0.6	p<0.01
36	Shipping Containers	9.54	9.98	0.44	p<0.02
37	Transportation	9.71	8.88	-0.83	p>0.05
38	Wholesale	9.66	9.71	0.05	p<0.04
39	Retail	8.38	9.19	0.81	p<0.05
40	Restaurants, Hotels, Motels	8.58	8.95	0.37	p<0.06
41	Other	8.88	9.39	0.51	p<0.07

Table 4.4, Panel A provides the mean and median of the cost of equity capital based on Gebhardt et al's. (2001) model. Specifically, a firm violating a debt covenant, on average,

experiences an increase in the cost of equity capital from 11.47 % to 12.43 %, which is an 8.36 % increase during the sample period 1996-2011. The difference is statistically significant at 1 percent. This reflects higher perceived operating risk implied by revised earnings forecasts and a change in stock prices following a covenant violation.

Similarly, Table 4.4, Panel B, C, and D present the estimates of cost of equity capital for the sample firms implied by earnings forecasts and stock prices one month before and after covenant violations based on Gode and Mohanram's (2001), Easton and Monahan's (2003), and the modified PEG- Easton's (2004) models, respectively. I observe similar patterns across all four models. That is, the implied cost of equity capital increases significantly for the sample firms after covenant violations. Table 4.4, Panel E reports the mean (median) level of four estimates of the cost of equity capital for violating firms. On average, the cost of equity capital for the sample firms experiences a statistically significant increase from 12.37 % to 13.42 % following a covenant violation, which is a 8.48 % increase.

Table 4.5 shows the results obtained from the random and matched samples based on propensity score matching method. Table 4.5, Panel A presents four estimates of the implied cost of equity capital for the random sample firms in violation of covenant while Table 4.5, Panel B presents estimates of the implied cost of equity capital for the matched sample firms. The results in Table 4.5, Panel A are generally consistent with those showed in Table 4.4. Firms with covenant violations in the random sample experience a 13.4% statistically significant increase in the cost of equity capital (from 12.39 % to14.05 %), while firms without covenant violation in the matched sample experience no significant change in the cost of equity capital over the same period.

Table 4.4 Change in Implied Cost of Equity Capital Following Covenant Violations

This table shows the change in the implied cost of equity capital following covenant violations estimated from four models introduced by Gebhardt, Lee, and Swaminathan(2001), Gode and Mohanram (2003), Easton and Monahan(2003), and Easton (2004). I obtain the model-based earnings forecasts and stock prices for one month before and one month after the violations to calculate the change in the implied cost of equity capital for violating firms in the sample. I use *t*-tests (Wilcoxon signed-rank test) to compare the means (medians) of two groups.

Model	**Full Sample**			
	Mean (%)		**Median (%)**	
	Before	**After**	**Before**	**After**
Panel A: Gebhardt, Lee, and Swaminathan (2001)	11.47	12.43	9.56	9.11
T-test (mean); Wilcoxon (median)				
Difference (*t*-statistics for *t*-test/ z-statistics for Wilcoxon)	0.963** *(-2.19)*		0.45* *(-1.68)*	
Panel B: Gode and Mohanram (2003)	12.73	13.66	12.36	13.35
T-test (mean); Wilcoxon (median)	0.93***		0.99**	
Difference (*t*-statistics for *T*-test/ z-statistics for Wilcoxon)	*(3.53)*		*(1.97)*	
Panel C: Easton and Monahan (2003)	12.96	14.06	13.68	16.54
T-test (mean); Wilcoxon (median)				
Difference (*t*-statistics for *t*-test/ z-statistics for Wilcoxon)	1.10** *(2.12)*		2.86 *(0.08)*	
Panel D: The Modified PEG Ratio by Easton (2004)	14.41	14.89	13.87	14.52
T-test (mean); Wilcoxon (median)	0.048**		0.65	
Difference(*t*-statistics for *t*-test/ z-statistics for Wilcoxon)	*(3.56)*		*(0.75)*	
Panel E: Average all four models	12.37	13.42	12.24	13.33
T-test (mean); Wilcoxon (median)	1.05**		1.09*	
Difference (*t*-statistics for *t*-test/ z-statistics for Wilcoxon)	*(2.86)*		*(1.64)*	

Table 4.5 Change in Implied Cost of Equity Capital Following Covenant Violations for Random Samples Based on the Propensity Score Matching Technique

I generate a random sample of 300 firms from the violating sample. I then create a matched sample of 300 firms from the non-violating sample based on the propensity score matching technique. This technique allows me to match non-violating firms on the basis of their estimated likelihood of violating covenants. I directly estimate firms' propensity to violate covenant based on covenant tightness (covenant slacks) and firm characteristics, and then I match violating firms to those that are not in violation of covenants during the same period. Slack is measured as the difference between the observed ratio and the minimum allowable ratio as indicated in a loan contract. The propensity score is calculated using a probit regression of covenant violation on the log of total assets, profitability, current ratio, leverage, coverage, market to book ratio, industry, and financial covenant slacks to control for borrower characteristics. I use *t*-tests (Wilcoxon signed-rank test) to compare the means (medians) of two groups.

Model	**Panel A: Random Violation Sample (N=300)**				**Panel B: Matched Sample Based on Propensity Score Matching (N=300)**			
	Mean (%)		Median (%)		Mean (%)		Median(%)	
	Before	After	Before	After	Before	After	Before	After
Gebhardt, Lee, and Swaminathan (2001)	10.90	12.73	9.70	9.15	7.73	7.61	7.78	7.76
T-test/ Wilcoxon (difference and p-value)	1.83*** (*p*-value<0.00)		-0.555 (*p*-value>0.1)		0.12 (*p*-value>0.1)		-0.02 (*p*-value>0.1)	
Gode and Mohanram (2003)	11.89	13.90	11.95	13.79	13.05	13.52	13.22	12.59
T-test/ Wilcoxon (difference and p-value)	2.01*** (*p*-value<0.00)		1.84* (*p*-value>0.05)		0.47 (*p*-value<0.01)		-0.63 (*p*-value>0.1)	
Easton and Monahan (2003)	13.08	14.96	15.50	17.74	12.21	12.75	9.34	10.25
T-test/ Wilcoxon (difference and p-value)	1.88*** (*p*-value<0.00)		2.24** (*p*-value<0.01)		0.54 (*p*-value>0.1)		0.91 (*p*-value>0.1)	
The Modified PEG Ratio by Easton (2004)	13.76	14.63	14.35	14.49	10.88	9.19	10.74	9.01
T-test/ Wilcoxon (difference and p-value)	0.87** (*p*-value<0.00)		0.14 (*p*-value>0.1)		-1.69 (*p*-value>0.01)		-1.73* (*p*-value>0.05)	
Means (four models)	12.39	14.05	12.88	13.79	10.96	10.76	10.27	9.90
T-test/ Wilcoxon (difference and p-value)	1.67** (*p*-value<0.00)		0.91 (*p*-value>0.1)		-0.19 (*p*-value>0.1)		-0.36 (*p*-value>0.1)	

Overall, the results in Table 4.4 and 4.5 provide evidence that firms are more likely to experience a significantly higher level of cost of equity capital resulting from higher perceived risk following a covenant violation as implied by analysts' earnings forecast revisions and a change in stock prices.

4.5.2 Covenant Violations and the Propensity of Equity Issuance

One of my predictions in this study is whether covenant violations have significant impact on the likelihood of equity issuance. This section presents the results from the logistic regression that examines whether the creditor requires the violating firm to issue new equity to lower leverage. Prior studies (Myers and Majluf, 1984; Shyam-Sunder and Myers, 1999; Hovakimian et al., 2001; Graham and Harvey, 2001; Baker and Wurgler, 2002; Alti and Sulaeman, 2012) show that firms with high market-to-book ratio (overvaluation or high level of misvaluation), high leverage ratio, high level of financial deficits, and high cumulative returns prior to SEOs are more likely to issue equity. For example, firms with high market-to-book ratios are often growing quickly and more likely to issue equity. Also, the market-to-book ratio can be used as a proxy for manager's perceptions of misvaluation, if the managers think investors are irrational and time the market by raising equity when the cost of equity is unusually low (Myers and Majluf, 1984; Baker and Wurgler, 2002). Therefore, I model the likelihood of issuing equity following a covenant violation during the sample period as a function of firms' market-to-book (*MB*) ratio, plus other control variables, including covenant violation dummy (*Viodummy*), cumulative market adjusted returns one year prior to the new offerings (*Pre_return*), leverage ratio(*Leverage*), financing deficit (*Deficit*), profitability (*EBITDA*), firm size (*Size*), and capital expenditure (*CAPEX*).

The logistic regression specification is as follows:

$$\Pr(\text{Equity issuance decision} = \text{Yes}) = \frac{1}{1+e^{-u}}$$

Where

$$u=\beta_0 + \beta_1(\mathit{Viodummy})+\beta_2 MB+ \beta_3 \mathit{Pre\_return}+ \beta_4 \mathit{Leverage}+ \beta_5 \mathit{Deficit}$$
$$+\beta_6 \mathit{Profitability} +\beta_7 \mathit{Size} + \beta_8 \mathit{CAPEX} + \varepsilon, \text{ (model 4.5.1)} \qquad (4.5)$$

The dependent variable is a dichotomous variable (*Seodummy*) that equals one if the violating firm does an SEO in the given year during three years immediately following a covenant violation, and zero otherwise. I obtain new equity offerings for the period 1996-2012 from SDC database. After matching and deleting missing data due to the constructions of control variables, I am able to identify a total of 3,707 seasoned equity offerings during the sample period, out of which 519 new offerings are conducted by firms that have experienced a financial covenant violation in the previous three years.

To address the concern that the history of concurrent increases in external funding needs and the market-to-book ratio are possibly affected by underlying firm characteristics rather than by market timing activity, I further decompose the market-to-book ratio into three components to better capture the likelihood of equity issuance if firms engage in equity market timing based on the Rhodes-Kropf, Robinson, and Viswanathan' (RKRV) (2005) market-to-book decomposition technique[9].

[9] See further discussions in chapter 3, section 3.4.2

$$\text{Pr (Equity issuance decision =Yes)} = \frac{1}{1+e^{-u}}$$

Where

$$u = \beta_0 + \beta_1 (Viodummy) + \beta_2 FSE + \beta_3 LRV + \beta_4 TSE + \beta_5 Pre\_return$$
$$+ \beta_6 Leverage + \beta_7 Deficit + \beta_8 Profitability + \beta_9 Size + \beta_{10} CAPEX + \varepsilon, \text{ (model 4.5.2)} \quad (4.6)$$

Table 4.6 presents the logistic regression results. I capture the overvaluation by using market-to book ratio (*MB*) in model 4.5.1 (equation 4.5) and firm specific error (market timing) (*FSE*) in model 4.5.2 (equation 4.6). Consistent with prior literature, the coefficients on *MB (FSE)*, *Pre_return*, *Leverage*, and *Deficit* are all positive and statistically significant at 1 percent, suggesting that firms with high market-to-book ratio or high level of misvaluation, high leverage ratio, high level of financing deficit, and high cumulative returns prior to SEOs are more likely to issue equity.

The magnitudes and signs of the coefficients on a set of control variables in both models are very similar if the market-to-book ratio is replaced with the firm specific error (*FSE*) and the other two components of RKRV's (2005) market-to-book decomposition (*TSE* and *LRV*). In addition, the coefficients on the covenant violation dummy (0.0533, *t*-value=1.98, and 0.0847, *t*-value=2.34 for model 4.5.1 and 4.5.2, respectively) are statistically positive in both models.

The positive coefficients indicate that violating firms are more likely to issue equity following a covenant violation during the sample period to reduce leverage. The results suggest that creditors have substantial influence over the financing decisions of covenant violators.

Table 4.6 Logistics Regression Analysis

Logistic regression analysis of the seasoned equity offerings (SEOs) decision as a function of firm's market to book (M/B) ratio (model 4.5.1), firm specific error (*FSE*), Long-run misvaluation (*LRV*), Time-series error (*TSE*) in model 4.5.2), covenant violation dummy, and other control variables including size, capital expenditures (*CAPEX*), financial leverage, financing deficit, tangible assets, pre-SEO market adjusted returns (Run-up) over the 12 months ending immediately before the year of SEOs, profitability. Independent variables are lagged one year before the SEO year. All variables are winsorized at 1st and 99th percentiles. The *t*-statistics are shown in parentheses.

	Model (4.5.1) coefficients (1)	Model(4.5.2) coefficients (2)
Intercept	-0.1197***	-3.2836***
	(-15.82)	*(-13.51)*
Viodummy	0.0533**	0.0847**
	(1.98)	*(2.34)*
MB (market to book)	0.2153***	
	(4.88)	
FSE (Firm specific error)		0.6545***
		(3.71)
LRV (Long-run value to book value)		0.8971***
		(3.66)
TSE (Time-series sector error)		0.1916
		(0.77)
Pre_Return (12-month returns before SEOs)	0.1601***	0.5425***
	(6.69)	*(4.86)*
Leverage (Financial leverage)	0.3921	0.6845***
	(2.96)	*(3.53)*
Deficit (Financing deficit)	0.2632	0.3429
	(0.82)	*(1.35)*
Profitability ($EBITDA_{t-1}$)	0.3958	0.6383
	(1.25)	*(1.87)*
$Size_{t-1}$	-0.0023**	-0.0350
	(-2.18)	*(-3.58)*
$CAPEX_{t-1}$(Capital expenditure)	0.4325	0.1361
	(0.49)	*(0.24)*
Pseudo R^2	0.0728	0.0948

4.5.3 Covenant Violation and the Underpricing of Seasoned Equity Offerings

Prior literature has documented significant underpricing in seasoned equity offerings (e.g., Corwin (2003, Mola and Loughan (2004)). SEO underpricing occurs when the offer price is lower than the closing price on the day prior to the offer date. Scholars have developed several theories to explain the underpricing of SEOs. For example, information asymmetry theory (e.g., Myers and Majluf (1984)) explains that managers are tempted to mislead outside investors by issuing equity when their stocks are overvalued.

Anticipating such a tactic, outside investors will discount the prices they are willing to pay for the firms' new shares. Thus, higher levels of information asymmetry should lead to higher levels of SEO underpricing (discount). Another explanation is that underwriters have an incentive to leave money on the table for outside investors during SEOs in order to get the job done, thus enjoying high reputation and recognition from customers. Prior empirical studies document that the major determinants of SEO underpricing include the level of information asymmetry, the level of uncertainty about firm value, underwriter reputation, relative offer size, and conventional underwriter pricing practices (Altinkilic and Hansen, 2002; Corwin 2003).

If a firm violates a loan covenant, the creditor may require the firm to lower its debt level by issuing new equity or refraining from new debt issues. In the former case, if the firm is forced by the creditor to issue new equity following the violation to lower leverage, it is expected that the firm would experience a higher level of SEO underpricing. In other words, if a firm is not able to offer new equity during a "window of opportunity" or during hot markets to reduce "the money leave on the able" during new equity offerings, it may have to offer a steep discount on new equity offerings following a covenant violation in order to avoid possibly severe actions from the lender. In addition, I hypothesize that the level of information asymmetry would

increase following the violation since outside investors may not know what actions the creditor would take to punish the borrower in the event of covenant breach. The prior literature on SEO underpricing shows that the higher level of information asymmetry is associated with the higher level of SEO underpricing.

In this section I analyze the effects of covenant violations on SEO underpricing for new offerings conducted during a three year period after covenant violation. Our hypothesis is that firms conducting new equity offerings following a covenant violation are more likely to experience a higher degree of SEO underpricing.

To test this hypothesis, I use the following regression specifications:

$$Underpricing = \beta_0 + \beta_1 Viodummy + \beta_2 PreCar + \beta_3 IPOUnderpricing + \beta_4 Volatility + \beta_5 Offersize + \beta_6 Rank + \beta_7 Size + \beta_9 NASDAQ + \varepsilon, \quad \text{(model 4.5.3) (4.7)}$$

$$Underpricing = \beta_0 + \beta_1 Viodummy + \beta_2 PreCar + \beta_3 IPOUnderpricing + \beta_4 Volatility + \beta_5 Offersize + \beta_6 Rank + \beta_7 Tick + \beta_8 Size + \beta_9 NASDAQ + \varepsilon, \quad \text{(model 4.5.4) (4.8)}$$

$$Underpricing = \beta_0 + \beta_1 Viodummy + \beta_2 PreCar + \beta_3 IPOUnderpricing + \beta_4 Volatility + \beta_5 Offersize + \beta_6 Rank + \beta_7 Tick + \beta_8 Size + \beta_9 Beta + \beta_{10} NASDAQ + \varepsilon, \quad \text{(model 4.5.5) (4.9)}$$

Our dependent variable is *Underpricing*, defined as the closing price on the offer day minus the offer price, divided by the offer price. I also use the second proxy for *Underpricing*, namely *Discount* for our regressions. *Discount* is the closing price on the day prior to the offer minus the offer price, divided by the closing price on the day prior to the offer.

Along with our variable of interest, *Viodummy*, I also include a set of explanatory variables that are widely adopted in the literature. First, *Volatility* variable, proxied for stock price uncertainty, is defined as the standard deviation of stock returns over the period of 30 trading days ending 10 days prior to the offer date. I expect a positive coefficient on *Volatility* since Corwin (2003) finds higher return volatility is associated with higher levels of underpricing. Second, *PreCar* variable, proxied for pre-offer price run up, is defined as the cumulative adjusted returns over the period of 5 trading days prior to the offer. I expect a positive coefficient on *PreCar* since the literature on SEO underpricing (e.g., Loughran and Ritter (2002)) has documented that the equity issuers are more tolerant of excessive underpricing if they simultaneously learn about a post market valuation that is higher than what they expected. Therefore, issuers who see greater recent increases in their stock price have the edge over their contracted underwriters in setting the offer prices. This also implies that pre-offer abnormal stock returns are positively related to the magnitude of the SEO underpricing.

In addition, I follow Corwin (2003) to control for the effects of price pressure with the variable *Offersize*, calculated as shares offered divided by the total number of shares outstanding prior to the offer. I also include *Tick*, which is a dummy variable equals to one if the decimal if the decimal portion of the closing price on the day prior to the offer is less than $ $0.25, and zero otherwise, to reflect the effects of rounded prices on SEO underpricing. Other control variables include *IPOUnderpricing*, measured as the average underpricing across all IPOs during the same month as the SEO and NASDAQ dummy variable that equals one if the issuers are listed on NASDAQ, and zero if on NYSE or AMEX at the time of offer. Finally, I use *Rank* to control for quality of underwriters. I obtain information on underwriters' ranking for the lead underwriter for each SEO in our sample from Jay Ritter's website.

Table 4.7 reports the results from univariate and multivariate tests of the effects of covenant violations on SEO underpricing. Table 4.7, Panel A shows that the mean and median of SEO underpricing of issuers with covenant violations are much larger than those of issuers without covenant violations. Specifically, the mean *Underpricing* (*Discount*) of issuers with covenant violations are 0.0342(0.0405), while the mean *Underpricing* (*Discount*) of issuers with covenant violations are 0.0285 (0.0348). The difference between the means of two samples is statistically significant at 1 percent.

With regard to multivariate analysis, Table 4.7, Panel B provides strong evidence to support my hypothesis. The coefficients on *Viodummy* are all positive and statistically significant at 5 percent for all three models. Specifically, these coefficients on *Viodummy* are 0.0052 (t=-2.05), 0.0053 (t=2.08), and 0.0047 (t=1.96) for model 4.5.3 (equation 4.7), model 4.5.4 (equation 4.8), and model 4.5.5 (equation 4.9), respectively. This suggests that creditors may require firms to issue equity to lower leverage during unfavorable market conditions, thereby resulting in a higher level of SEO underpricing.

Other control variables are consistent with prior studies. For example, the signs of *PreCar*, *Volatility*, and *Offersize* are all positive and statistically significant. SEO underpricing increases with volatility of stock returns prior to SEOs, relative offer size, and pre-offer abnormal returns. The negative coefficients on *Rank* suggest that SEO underpricing decreases with underwriters' reputation. Also, issuers listed on NASDAD stock exchange experience higher levels of SEO underpricing.

Table 4.7 The Effects of Covenant Violation on SEO Underpricing

Panel A presents *t*-test analysis of the effects of covenant violations on SEO underpricing. Panel B lists coefficients (*t*-values) from OLS regressions of SEO underpricing on violation dummy and a set of control variables. *P*-values are based on White's (1980) heteroskedasticity consistent standard errors. All continuous variables are winsorized at the 1st and 99th percentiles, respectively

Panel A: the *T*-Test Analysis

	Mean (SEO Underpricing)	**Mean (SEO Discount)**
Group 1 (519 SEOs of violating firms)	0.0342	0.0405
Group 2 (3,188 SEOs of non-violating firms)	0.0285	0.0348
Difference (Group 2-Group 1)	-0.00572**	-0.0059***
t-value	*(-2.46)*	*(-3.04)*

Panel B: Multivariate Analysis

Model	**Model (4.5.3)**	**Model (4.5.4)**	**Model (4.5.5)**
Intercept	-0.1204***	-0.1197***	-11.99
	(-11.23)	*(-11.13)*	*(-11.15)*
Violdummy	0.0052**	-0.0053**	0.0047**
	(2.05)	*(-2.08)*	*(1.96)*
PreCar	0.1603***	0.1601***	0.1600***
	(19.48)	*(19.45)*	*(16.45)*
IPOUnderpricing	-0.0040	-0.0041	-0.0040
	(-1.03)	*(-1.02)*	*(-1.03)*
Rank	-0.0023***	-0.0023***	-0.0023***
	(-2.93)	*(-2.93)*	*(2.98)*
Volatility	0.2532***	0.2527***	0.2371***
	(6.40)	*(6.93)*	*(5.86)*
Offersize	0.0070**	0.0069**	0.0071**
	(2.26)	*(2.26)*	*(2.32)*
Tick		-0.0015	-0.0015
		(-0.75)	*(-0.74)*
Nasdaq	0.0126***	0.0126***	0.0116***
	(6.06)	*(6.04)*	*(5.34)*
Beta			0.0017**
			(1.98)
Adj. R^2	0.2272	0.2292	0.2225

4.6 Conclusion

This study examines the impact of covenant violations on the implied cost of equity capital and underpricing of seasoned equity offerings conducted during the period immediately following covenant violations. Using a unique data set with 1,045 first-time covenant violations from 1996-2011 of the US public firms, I perform several robustness tests using different models in estimating the cost of equity capital implied by analysts' earnings forecasts, stock prices, and accounting data and find that the violating firms on average experience a 8.48 % increase in their implied cost of equity capital.

In addition, I also find a higher level of SEO underpricing for equity offerings conducted by violating firms during the period immediately following covenant violations. This suggests that creditors may require violating firms to issue equity to lower leverage, thereby resulting in a higher degree of SEO underpricing through the SEO episodes

Chapter 5

Summary and Conclusion

The three essays of this dissertation contribute to the current literature by finding new determinants of SEO underpricing based on new mechanisms that affect their pricing. In the first essay, we (co-authored with Oscar Varela) examine the effects of earnings smoothing on the pricing of SEOs. We explore a new role for earnings smoothing prior to SEO episodes based on signaling theory. Somewhat in contrast with the earnings smoothing literature based on the managerial opportunism hypothesis, we provide evidence that earnings smoothing may be used to signal firm quality to outside investors if firms are able to smooth their earnings for long periods of time. Specifically, we sorted all SEO firms during the period 1989-2010 into quartiles based on the level of earnings smoothing prior to SEOs and tested whether firms with a long period of time with smooth earnings experience a lower degree of SEO underpricing. The findings confirm our hypotheses that SEO firms with high level of earnings smoothing experience a lower degree of SEO underpricing. Also, the stock returns and operating performance of firms with higher levels of earnings smoothing are higher than those of firms with lower levels of earnings smoothing at least three years subsequent to the SEO.

In an attempt to explore a new mechanism that affects SEO underpricing, I further examine the roles of lines of credit in the market timing of the SEO. Using a unique dataset with detailed information on lines of credit, I am able to investigate whether firms accessing lines of credit would have an option to temporarily delay equity offerings until the market conditions become more favorable. I find evidence that lines of credit allow firms to actively time the market. The results are consistent with my conjecture that while not perfect substitutes for cash,

lines of credit affect the pricing behavior of SEO firms and create more value for current shareholders by reducing the degree of SEO underpricing. The results hold regardless of different timing measures and proxies for underpricing.

Finally, I examine the direct effects of covenant violations on SEO underpricing and quantify the changes in the cost of equity capital following covenant violations. Using well adopted models for estimating the implied cost of equity and a unique dataset consisting of 1,045 first-time covenant violations from 1996 to 2012, I find that firms that violate a covenant, on average, experience a 8.48 % increase in the implied cost of equity. I also find a higher level of SEO underpricing for seasoned equity offerings conducted within two years following covenant violations. This suggests that creditors may require or force violating firms to issue equity to lower leverage, thereby resulting in a higher degree of SEO underpricing for the violating firms.

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Appendix 1: Variable Definitions

The Altman Z-Score: The measure of a company's health and likelihood of bankruptcy based on Altman (1968). The Z-score is constructed as follows: Z = 1.2*(*WC/TA*) + 1.4*(*RE/TA*) + 3.3*(*EBITDA/TA*) + 0.6*(*ME/TL*) + 1.0* (*Sales/TA*). *WC* is defined as working capital. *TA* is total assets. *RE* is retained earnings. *EBITDA* is earnings before interest, taxes, depreciation and amortization. *ME* is market equity. *TL* is total liabilities.

Beta: Computed from a regression of firms' monthly raw returns on the monthly value-weighted market returns over the rolling five year window ending in the current fiscal year of the offer date.

Book-to-market (BM): The natural log of the ratio of book value of equity to market value of equity.

Cash flow: Net income minus accruals.

Cash flow volatility: Standard deviation of quarterly cash flows over the five year period prior to the offer.

Correlation: The correlation between quarterly cash flows and accruals over the five year period prior to the offer date.

DA: Total discretionary accruals over one year prior to the offer date.

EPS: Earnings per share (basic) / excluding extraordinary items.

IPOunderpricing: The average underpricing across all IPOs during the same month as the SEO, where the monthly underpricing estimates for IPOs are obtained from Jay Ritter's website.

I obtain underwriter ranking sample jay Ritter's website. Ritter refines Carter and Manaster's (1990) ranking method to construct a new ranking database for major underwriters and underwriters are ranked based on a 0-9 scale.

The KZ Index: The linear combination of five variables: debt to total capital (positive relationship), dividends to capital (negative relationship), cash holdings to capital (negative relationship), cash flow to capital (negative relationship), and Tobin's Q (positive relationship) (Equation 3.9). More constrained firms have a higher KZ index and vice versa.

KZ Index = -1.002 x (*Cash Flows / K*) + 0.283x Q + 3.139x (*Debt / Total Capital*)

-39.368 x (*Dividends / K*) -1.315 x (*Cash / K*)

Market-to-Book (MB): (Market value of equity + book value of debt)/total assets.

Ln(price): Natural log of of the closing price on the day prior to the offer date

Leverage: A firm's leverage defined as the ratio of total liabilities to asset

Nasdaq: The dummy variable that equals one if the firms listed on the Nasdaq at the time of offer and zero otherwise.

Ohlson O-Score: The measure of a company's health and likelihood of bankruptcy based on Ohlson (1980). Ohlson O-score= -1.32-0.407**Size*+6.03**TLTA*-1.432**WCTA*+0.076**CLCA*-1.72**OENEG*-2.37**NITA*-1.83**FFOLT* +0.285*I*NTWO*-0.521**CHIN*.

Size or market assets are defined as market total liabilities plus market equity (price times shares outstanding) divided by consumer price index (CPI). *TLTA* is defined as the book value of debt divided by market assets. *WCTA* is working capital divided by market assets. *CLCA* is current liability divided by current assets. *ONENEG* is one if total liabilities exceeds total assets and is zero otherwise. *NITA* is net income divided by assets. *FFOLT* is the funds from operations divided by liability. *INTWO* is equal to one if net income is negative for the last two years and zero otherwise. *CHIN* is defined as *(NI-NIt-1)/(*absolute*(NI)*+absolute *(NIt-1)*, where *NI* is net income for the most recent quarter.

Offersize : Shares offered divided by the total number of shares outstanding prior to the offer.

PreCar: Cumulative market adjusted returns over the period of five days prior to the offer date.

Returns Volatility: the standard deviation of stock returns over the period of 30 trading days ending 10 days prior to the offer.

ROA : The income before extraordinary items divided by average total assets

Size: The natural log of market value of equity, measured at the end of fiscal year become available for the monthly regressions.

Smooth: The ratio of standard deviation of net income (scaled by average total assets) divided by the standard deviation of cash flows from operation (scaled by average total assets). We scale the volatility of net income by cash flow volatility to measure the extent to which accruals are possibly used to smooth out the underlying volatility of the firm's operation. Our primary measure of net income is net income before extraordinary item scaled by average total assets. Cash flows equal net income less accruals. Accruals are the change in current assets minus the change in cash minus the change in current liabilities plus the change in shorter debt minus depreciation.

Tick: The dummy variable taking the value 1 if the decimal portion of the closing price on the day prior to the offer is less than $ 0.25, and zero otherwise.

Total_accrual: Total discretionary accruals over the five year period prior to the offer, scaled by average total assets.

Underpricing: The closing price on the offer day minus the offer price, divided by the offer price.

Underpricing_discount: the closing price on the day prior to the offer minus the offer price, divided to the closing price on the day prior to the offer.

Appendix 2: Copyright Permission

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June 25, 2013

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Vita

Anh Duc Ngo (Ngô Đức Anh), the youngest son of Mr. Ngô Văn Kiển and Mrs. Bùi Thị Chinh, was born and raised in Hanoi, Vietnam. He earned a B.A in economics with honors from National Economics University (NEU) in 1998. Upon graduation he joined NEU as a lecturer. He was then awarded a full study abroad government scholarship from the Ministry of Education and Training of Vietnam. The scholarship financially enabled him to pursue an MBA degree at the University of New Orleans from 2002 to 2004. After earning his MBA degree, he went back to Vietnam and then taught at NEU from 2004 to 2008. During that period, he was also a researcher at the Vietnam Development Forum (VDF), a joint research project between National Economics University (Vietnam) and the National Graduate School of Policy Studies (Japan). At the VDF, he actively participated in several research projects on supporting industries and pro-poor economic development in Vietnam.

Mr. Ngo entered the Ph.D Program in International Business with a major in finance at the University of Texas at El Paso in 2008. Again, he was awarded a full doctoral scholarship from the Ministry of Education and Training of Vietnam for pursuing a doctoral degree abroad. During the Ph.D program, Mr. Ngo published several publications. He has also presented his research at several conferences including the AAA, EFA, FMA, MFA, SFA, and SWFA Annual Meetings. In 2012, he was selected as the first recipient of the Paul L. Foster and Alejandra de la Vega Foster Doctoral Fellowship.

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