Two Essays on Empirical Tests Related to Capital Structure Theory

by

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A Thesis submitted to the Faculty of Graduate Studies of

The University of Manitoba

in partial fulfillment of the requirements of the degree of

MASTER OF SCIENCE

Department of Accounting and Finance

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ABSTRACT

This paper discusses capital structure theories, with special attention to partial-adjustment model. Strategic waiting theory of IPO firms, and its relation to market timing theory are also discussed. Two empirical tests related to capital structure theory are included. First one is a test on the relation between a firm's strategic waiting behavior in IPO market and its stock return. Second one is on the relation of a firm's strategic waiting behavior in IPO market and its subsequent capital structure decision.

Chapter 2 tests strategic waiting theory for initial public offering (IPO) firms, with a Canadian sample of 1,005 IPOs from 1985 to 2010, by analyzing their long-run performance, and I find there is weak evidence that firms issued in hot IPO cycles have better performance in 3 to 5-year horizon, but there is some evidence supporting the theory in a longer horizon. More importantly, I find an inverted U-shaped relation between the firm's long-run performance and the probability of market being in hot IPO cycle while issuing, which suggests a non-linear relationship. My findings suggest that country specific factors and empirical methods may affect the results.

Chapter 3 investigate whether firms issued in hot IPO cycles, which supposedly with higher portion of high quality firms that strategically waited longer in IPO market than low quality firms do (Colak & Gunay, 2011), also differ in speed of adjustment (SOA) toward target debt ratios and in debt leverage levels. This chapter uses dynamic panel data with a system GMM estimator, and dynamic panel data with fractional dependent variable (DPF) estimator, on 122,454 firm-year data from year 1965 to 2013. I find that the firms issued in hot IPO cycles on average have about 12%-260% relatively higher SOA depending on econometric model used, and have no significant difference in terms of leverage levels, however, for firms in different age groups, there is weak evidence in favor of strategic waiting theory.

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ACKNOWLEDGEMENTS

I'd like to express my sincere appreciation to my committee members, Dr. Usha Mittoo, Dr. Steven Zheng, Dr. Jeffrey Pai and Dr. Xikui Wang, for their time and assistance with this project. I'd like to thank Dr. Gady Jacoby, Dr. Alexander Paseka for their useful inputs. I'd like to thank Mr. Ji Zhou for his suggesting on a technical issue in GMM estimation.

I'd like to thank Dr. Hikmet Gunay for introducing his strategic waiting theory to me. I'd also like to thank Dr. Milton S. Boyd, Dr. Brian T. Oleson and Dr. Yunmi Kim for their support. I am heavily indebt to Dr. Barry T. Coyle for guidance and encouragement.

CHAPTER

ONE

INTRODUCTION

This paper discusses capital structure theories, with special attention to partial-adjustment model. Strategic waiting theory of IPO firms, and its relation to market timing theory are also discussed. Two empirical tests related to capital structure theory are included. First one is a test on the relation between a firm's strategic waiting behavior in IPO market and its stock return. Second one is on the relation of a firm's strategic waiting behavior in IPO market and its subsequent capital structure decision.

1.1 Capital structure

Capital structure is the way a firm finances its assets through a combination of equity (stock) and debt (bond). Is there a debt-equity ratio would maximize a firms' market value, and a firm would take this ratio as a target? What factors determine the actual leverage ratio for a firm? The major capital structure theories include MM theory, trade-off theory, signal theory, pecking order theory, and market timing theory. Some theories recognize that firm has a target leverage ratio, and argue that a firm is motivated by maximizing its market value (e.g., trade-off theory, free cash flow theory, agency theory); some theories recognize that firm has a target leverage ratio, but argue that a firm is motivated by minimizing a certain kind of cost (e.g., free cash flow theory, agency theory); some theories recognize no target ratio, and take other considerations as deterministic factors of a firm's capital structure decision (e.g., pecking order theory, signalling theory, market timing theory), see Fig. 3.1. However, there is no universal capital structure theory that can explain all empirical evidence. A realistic concern nowadays is that under what conditions, which theory would prevail (Graham & Leary, 2011).

1.2 Why partial-adjustment model is still relevant?

Chapter 3 is an empirical test on the difference in terms of SOA between firms issued in hot and non-hot IPO cycles, and SOA evaluation is based on partial-adjustment model. The partial-adjustment model is a development over statistic trade-off model. It recognize the the existence of adjustment cost which is ignored in the statistic trade-off model. By adding such cost, it is more realistic and as a result it can address many issues not explained by the statistic trade-off model.

However, partial-adjustment model has many deficiencies. First, its assumption is very restrictive. It assumes that each period's leverage ratio is driven by the divergence between actual and target leverage ratios, and it lacks a full consideration of capital structure dynamics. Many dynamic trade-off models relax this assumption. Costly adjustment models uses initial leverage and recapitalization boundaries instead of leverage targets, (e.g., Fischer, Heinkel, & Zechner, 1989; Goldstein, Ju, & Leland, 2001). Endogenous investment models assume that financing decisions are determined mainly by their effects on future investment and financing choices instead of market frictions such as taxes and bankruptcy costs (e.g., Mauer & Triantis, 1994; DeAngelo, DeAngelo, & Whited, 2011). Second, empirical results impose considerable challenges on partial adjustment model. Earlier research such as Fama and French (2002) find the the speed of adjustment (SOA) to be between 9% to 18%, and they call it a “glacial readjustment." Later, Flannery and Rangan (2006) find SOA to be around 38% using fixed effect model, Lemmon, Roberts, and Zender (2008) also find 39% with FE model. However, recent literature criticizes the properness of the fixed effect model. For example, Elsas and Florysiak (2013) developed a dynamic panel fractional (DPF) model, which is in essence a doubly-censored Tobit model, and estimate SOA to be around 26%. Third, trade-off theory, which partial-adjustment model built upon, is challenged by a group of theories that question the existence of optimal capital structure. For example, market timing theory (Baker & Wurgler, 2002) argues that a firm’s financing decisions are driven by factors such as market timing incentives. A survey conducted by Graham and Harvey (2001) shows that most CFOs do not have target leverages in mind.

Facing so many challenges, one may wonder whether the partial-adjustment is still relevent? In my opinion, it is still has theoretical and empirical supports (e.g., DeAngelo et al. (2011) developed a model that allow slow adjustment speed). More importantly, it is still a useful framework for testing firm properties other than estimating SOA itself. It is more a matter of when and under what circumstance the partial-adjustment model can apply (Graham & Leary, 2011).

1.3 Strategic waiting theory of IPO firms

Colak and Gunay (2011) developed a strategic waiting model for IPO firms. They assume there are two kinds of firms in the IPO market: high quality firms and low quality firms. Under information asymmetry, prior to IPO the investors do not know what types the firms belong to, but the managers of the firms know their own types. Suppose the fair price for a share of high quality firm is P_H, for a share of low quality firm is P_L. On average investors are willing to pay a price P for a share, where $P_L <$

$P < P_H$. High quality firms are reluctant to sell their shares through IPO at a discount, and, therefore they wait until the market is confirmed to be in a “hot issue" cycle when the investors are paying a premium for a share. Colak and Gunay showed that, under reasonable parameter assumptions, high quality firms have incentives and can afford the waiting, while low quality firms do not.

Compared with market timing theory, Colak and Gunay (2011) not only distinguish firm quality and their abilities to “timing" the market, but also assume the information asymmetry on market condition. In their model, the true market condition is unknown, all firms could only guess based on the IPO activities observed. In this sense, strategic waiting theory is a development of market timing theory.

Chapter 2 is a test on the relation between a firm’s strategic waiting behavior in IPO market and its stock return. Chapter 3 is on the relation of a firm’s strategic waiting behavior in IPO market and its subsequent capital structure decision.

1.4 Dynamic panel fractional (DPF) estimator

Many econometric methods, including OLS, IV, GMM, fixed effect model etc, have been applied to estimate SOA in partial-adjustment model in previous literature. However, recent paper by Elsas and Florysiak (2013) point out all the results from previous methods are biased, and they provide a new method called dynamic panel fractional (DPF) estimator to address the two issues in the data: the data is a dynamic panel data in nature, and the variable being explained is censored.

The DPF estimator uses a doubly-censored Tobit specification with corner observations at 0 and 1, with a lagged dependent variable. DPF estimator employs a latent variable specification and estimates the regression equation. Loudermilk (2007) shows that in non-linear panel models there is no known transformation to eliminate unobserved fixed-effects (heterogeneity), therefore Elsas and Florysiak’s DPF estimator specifies a conditional distribution for unobserved heterogeneity as suggested by

Loudermilk (2007). Elsas and Florysiak demonstrate with simulated data that the DPF estimator is unbiased when dealing with censored data, while other estimators such as OLS, FE, Fama-MacBeth, Blundell and Bond, LD, LSDVC are all biased. In chapter 3, I use DPF estimator to estimate the SOA.

CHAPTER

TWO

STRATEGIC WAITING IN THE IPO MARKETS: EVIDENCE FROM CANADA

This chapter tests strategic waiting theory for initial public offering (IPO) firms, in a Canadian sample of 1,005 IPOs from 1985 to 2010, by analyzing their long-run performance, and I find there is weak evidence that firms issued in hot IPO cycles have better performance in 3 to 5-year horizon, but there is some evidence supporting it in a longer horizon. More importantly, I find an inverted U-shaped relation between the firm's long-run performance and the probability of market being in hot IPO cycle while issuing, suggests a non-linear relationship. My findings suggest that country specific factors and empirical methods may affect the results.

2.1 Introduction

The phenomenon of clustering of initial public offerings (IPOs) has been widely observed and discussed in the finance literature (e.g., Ibbotson & Jaffe, 1975). However, the reason for the hot and cold market cycles is still not clear, and little research has been done on whether firm performance differs based on the hot or cold cycle IPO. Baker and Wurgler (2002) shows that a firm's equity-issue decisions is mainly driven by market timing attempt, and a firm's future performance does not seems to depends on whether the IPO is made in hot or cold cycle. In a recent paper, Colak and Gunay (2011) develop the theory about the link between when a firm goes public and its future performance. They examine clustering of IPOs with a learning process of issuers from a game theory perspective. They assume that the management has private information about the quality of their firm, and both high-quality and low-quality firms are constantly learning the status of the market through a Bayesian process before going public. Colak and Gunay have two main predictions. First, both low and high-quality firms have a tendency to strategically delay their initial public offerings until a favorable market condition is confirmed. Second, separating equilibrium in IPOs exists: lower quality firms will issue ahead of higher quality firms in the expanding cycle. Their first conclusion is consistent with a large number of studies in the previous literature on market timing (e.g., Graham & Harvey, 2001; U. Mittoo & Zhang, 2007). Their second conclusion is innovative, and they tested it with a sample of 9,013 IPOs in U.S. between 1973 and 2007 and found supporting evidence. The strategic waiting theory is important because it can help explain why the hot and cold market cycles exist and the firm's IPO timing decision within a hot IPO cycle.

This chapter extends the literature by testing the strategic waiting theory with Canadian IPO data. Canadian data is ideal for this testing this theory for two reasons. First, Canadian and U.S. capital markets are closely related, for example a large number of Canadian firms cross list on the U.S. exchange (see e.g., U. R. Mittoo, 2006). Thus, I will expect strategic waiting phenomenon should also be observed in Canada similar to that in United States. Second, Canadian data is suitable for an out-of-sample robustness check for strategic waiting theory because of many distinctive characteristics of

Canadian markets, such as lax delisting rules and greater market capacity to refinance non-profitable firms (Carpentier & Suret, 2011). This chapter tests strategic waiting theory with 1,005 Canadian IPOs and performance data between 1985 and 2010. There are two important findings. First is that Canadian data requires a longer horizon to support the prediction of strategic waiting theory compared with 3 to 5-year horizon in the case of U.S. data. Second, contrary to theoretical prediction, many low-quality firms issue after high-quality firms did, and I document an inverted U-shaped relation between the firm quality and the possibility of market being in hot IPO cycle. The intuition behind the second result is that, there are two kinds of low-quality firms, the first kind of low-quality firms are indeed more impatient than high-quality firms when going public and issue before high-quality firms as predicted by the strategic waiting theory; the second kind of low-quality firms (pure pretenders) are even more patient than high quality firms, they wait until the IPO cycle reached its summit, and take advantage of the hot market to sell their shares. However, as time goes by, after about 6 years (they can live so long as a result of Canada's lax delisting rules), as these pretenders die out, the trend that real high quality firms out perform low quality firms become evident. These two findings show that country-specific factors are also likely to affect IPO decisions. In addition, the nonlinear inverted U-shaped relation suggests the need for extending the theoretical model. I also develop a measure of market hotness using Markov-switching model, which is better than the simple dichotomous measure used in Colak and Gunay (2011), and this precise measure of market hotness provides better proxy of hot market to test their implications.

Please note that the method used in this chapter to compare average stock performance of different groups of firms is not the best method to test the strategic waiting theory of IPO firms. Even if I find that firms issued in hot IPO cycles underform the firms issued in non-hot IPO cycles, I can not prove strategic waiting theory to be wrong. The only valid way is to do a matching and comparison (e.g., nearest-neighbor matching), compare two matched firms only differ in timing of IPO (e.g., in same industry, has same firm characteristics prior to IPO, the only difference is that one issued in hot IPO cycle while the other one issued in non-hot IPO cycle), and test whether difference in terms of stock return exists. But this matching method is very hard to implement. However, if I can show on average stock return is higher for the group of firms issued in hot IPO cycle, then I find supporting evidence consistent with the strategic waiting theory.

The following section describes the data and testing methods; section three reports and discusses empirical results, and section four provides summary and conclusion of the paper.

2.2 Data and methodology

2.2.1 Data

The IPO data consists of 5,662 Canadian IPOs between January 1975 and October 2011 from Securities Data Company (SDC) database. The performance data of IPO firms includes 5,355 firms with 393,068 monthly returns between January 1, 1985 and December 31, 2010 from Canadian Financial Markets Research Centre (CFMRC) database. In order to track the long-run performance of IPO firms, I match IPO data and performance data using Committee on Uniform Security Identification Procedures (CUSIP) digits. I also check the company names from the both data bases manually to ensure matching correctly, and 1,005 firms can be matched in both data.

As the first step, I use market index model. I use CFMRC monthly value weighted index from 1985 to 2010 as the market returns in the market index model, and CFMRC monthly equal weighted index as a robustness check. As the further step, Fama-French three factor model can be used for robustness check. Canadian monthly Fama-French factors from 1990 to 2009 can be obtained from the homepage of Professor Claude

Francoeur at HEC Montreal (Francoeur, 2010).

2.2.2 Methodology

A major difficulty in Colak and Gunay (2011) paper is to decide when a firm's IPO intention begins, and this starting point in time is critical for measuring the length of strategic waiting. In cold or declining IPO cycle, high-quality firms and low-quality firms have a pooling equilibrium that is both kinds of firms do the same thing: issue immediately to take advantage of today's higher IPO price compared with declining price of tomorrow; therefore no strategic waiting will happen in cold IPO cycle. In hot cycle, however, high-quality firms can benefit and afford waiting longer aiming at a higher issuing price tomorrow. However, I can only observe the date of a firm's IPO; not the starting date of a firm's IPO intention. Colak and Gunay (2011) deal with the difficulty by introducing a very strong assumption that all the firms begin their "intentions" of IPO at the beginning of each hot IPO cycle. The part 1 of the Figure 4 illustrates the ideal assumption of Colak and Gunay (2011) paper, where both high-quality and low-quality firms start their "intentions" of IPO at the beginning of a hot IPO cycle, and high-quality firms wait longer. The part 2 of the Figure 4 illustrates what could actually happen if I recognize the assumption is too strong. More likely, an unobserved intention of IPO begins randomly across a rising IPO cycle, therefore issuing in the later part of a rising IPO cycle cannot guarantee the strategic waiting time of a firm is longer. This fact would seriously weaken the validity of the empirical testing method of Colak and Gunay (2011) paper. In their paper by using survival analysis, they test if the IPO firms with longer "survival time" (i.e. strategic waiting time) until "fail" (i.e. IPO) would have a better performance. In fact what is really being tested is if the IPO firms issuing in the later part of a rising IPO cycle would have a better performance.

Another difficulty in Colak and Gunay (2011) paper is identifying the stages of an

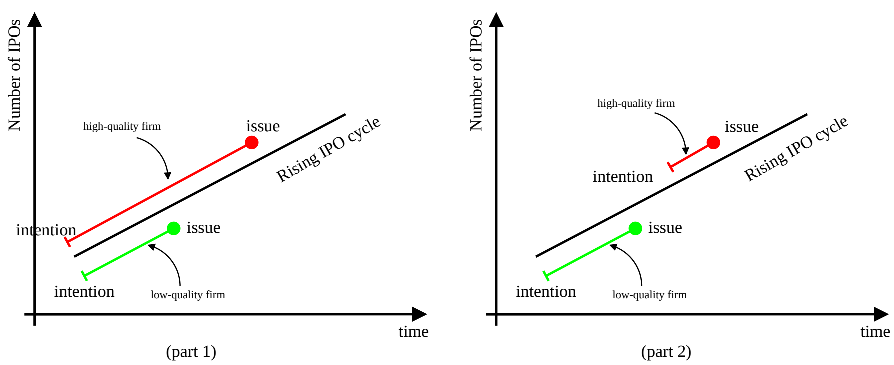


Figure 2.1: Diagram illustrating empirical testing assumptions

The part 1 of the diagram illustrates the ideal scenario of Colak and Gunay (2011) paper, where both high-quality and low-quality firms start their "intentions" of IPO at the beginning of a hot IPO cycle, and high-quality firms can benefit and afford waiting longer. The part 2 of the diagram illustrates what could actually happen if I recognize the assumption "all the firms begin their `intentions' of IPO at the beginning of a hot IPO cycle" is too strong. More likely, the unobserved intention of IPO begins randomly across a rising IPO cycle, therefore issuing in the later part of a rising IPO cycle cannot guarantee the strategic waiting time of a firm is longer. This fact would seriously weaken the validity of the empirical testing method of Colak and Gunay (2011).

IPO cycle. Ideally, what should be used are the subjective ex-ante estimations of the stages of an IPO cycle of individual firms. What are actually used are the objective ex-post estimations of the IPO cycle by using the IPO numbers at a certain period of time, which would introduce a measurement error.

To avoid the above two difficulties, I use an alternative method. In order to avoid measuring the unobserved starting points of "intentions" of IPO, I assume the "intentions" begins randomly across time horizon.

> Assumption 1: The intended IPO Firms start their "intentions" of initial public offering randomly across time.

Admittedly firms' "intentions" of IPO may be influenced by the condition of IPO market, but this assumption is much more realistic than assuming all the firms begin their intentions at the same time. In order to avoid identifying the subjective ex-ante estimations of the stages of an IPO cycle of individual firms, I assume the ex-post estimation of the hotness the market using Markov-switching method is consist with the subjective ex-ante estimations of the stages of an IPO cycle of individual firms.

> Assumption 2: The ex-post estimation of the hotness of the IPO market using Markov-switching model is positively related with the subjective ex-ante estimations of the likelihood of being in a hot IPO cycle of individual firms.

Under these two assumptions, I directly relate the likelihood of being in a hot IPO cycle with the stock performances. I argue that if strategic waiting theory holds, high-quality firms have a better chance of issuing in hot cycle because they are more patient. If this argument holds, I expect to see that

> Prediction 1: On average firms issuing in hot cycle would outperform firms issuing in non-hot IPO cycle.

Because low-quality firms tend to accept current market condition they face once they decide to go public, high-quality firms tend to wait for more favorable market condition, as a result, high-quality firms are more likely to issue in hot market cycle than low-quality firms. Consequently firms that issued in hot cycle would outperform firms issued in non-hot cycle. In the following sections I test this prediction and I find that this prediction holds for horizons longer than 6 years.

I also expect to see a monotonically increasing relation between the likelihood of being in hot cycle when issuing and the stock performance, if I group the firms according to the hotness of market.

> Prediction 2: By grouping the firms according to the hotness of IPO market when issuing, I expect to see a group issued in hot market will outperform a group issued in cold market.

I divided the firms into 10 groups according to the hotness of IPO market when the firms went public. If the sample size is large enough, the within group noises would cancel out and for every group as a whole there would a monotonic positive relation between the hotness of market when issuing and the long-run performance. In the following sections I test this prediction and find that the relation is not monotonically increasing, but a inverted U-shape curve. The complexity could be the result of multiple factors. For example, market timing attempts of firms will result in many low-quality firms be attracted by very hot market and decide to go public at the peak of market; another explanation is that strategic waiting theory itself needs extension to allow this non-linear relation.

2.2.3 Identifying IPO cycles

Following Colak and Gunay (2011) paper, I begin with identify IPO cycles. I first take the 4-quarter moving average of the quarterly IPO issuance observations. Then, I identify a rising IPO cycle as the period when the moving average has risen for at least

Table 2.1: Quarterly Number of IPO of Canadian Firms in Domestic Marketplace

Year	Q1	Q2	Q3	Q4	Total
1985	1	0	3	2	6
1986	47	40	66	156	309
1987	85	88	150	189	512
1988	128	150	109	73	460
1989	62	77	49	45	233
1990	26	17	9	14	66
1991	8	17	12	23	60
1992	16	12	10	16	54
1993	31	49	91	91	262
1994	47	73	42	52	214
1995	32	34	53	48	167
1996	54	50	57	85	246
1997	68	107	77	108	360
1998	62	69	45	52	228
1999	41	53	39	51	184
2000	40	51	49	77	217
2001	53	51	27	39	170
2002	35	43	34	33	145
2003	19	32	35	60	146
2004	51	67	46	83	247
2005	67	64	62	76	269
2006	76	65	69	62	272
2007	77	55	73	57	262
2008	98	49	45	26	218
2009	24	23	18	38	103
2010	37	41	20	38	136
2011	46	31	30	9	116
Total	1,331	1,408	1,320	1,603	5,662

three back-to-back quarters. Table 1 reports the quarterly IPO numbers, and Figure 1 visualize the quarterly IPO activity and its 4-quarter moving average. Different from Colak and Gunay (2011) paper, the IPO cycles will only be used in an auxiliary test if firms issuing in rising (hot) cycle would outperformance firms issuing in declining (cold) cycle. See Table 2.1 and Fig. 2.2.

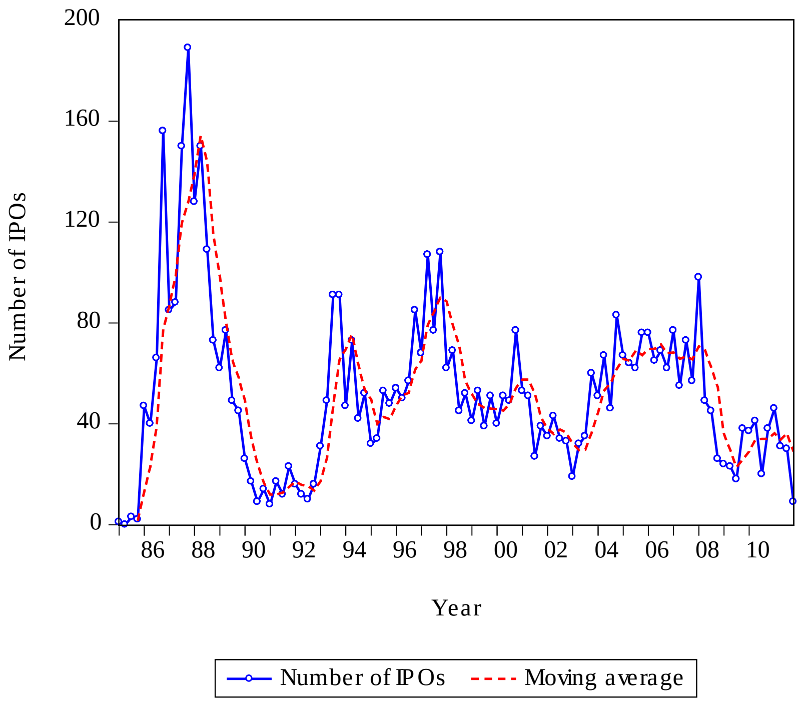


Figure 2.2: Quarterly Number of IPO and Four-quarter Moving Average Number

Blue line with circles shows the quarterly IPO numbers of Canadian markets from 1986 to 2012, and the red dashed line visualizes the 4-quarter moving average of IPO numbers. See page 13 for more discussion.

2.2.4 Abnormal returns

The quality of a firm is measured by its abnormal returns, and the abnormal return is computed by the actual return minus the normal return. Two methods are used to model the normal return: first method is market index model, i.e. simply use CFMRC monthly equal weighted/value weighted index from 1985 to 2010 to model normal return; second method which is used as a robustness check is Fama-French three-factor model (e.g., Fama & French, 1993, 1996),

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i \cdot SMB + h_i \cdot HML + \varepsilon_{it} \tag{2.1}$$

Here R_{it} is the stock's actual return, R_{ft} is the risk-free return rate, and R_{mt} is the return of market portfolio. The factor β_i is analogous to the classical β_i but not equal to it, since there are now two additional factors to do some of the work. SMB stands for "small (market capitalization) minus big" and HML for "high (book-to-market ratio) minus low"; they measure the historic excess returns of small caps over big caps and of value stocks over growth stocks. A relatively shorter period (1990 to 2009) of Canadian monthly Fama-French factors data are used because of the limitation of data availability.

2.2.5 Cumulative Abnormal Return

Firm j's cumulative abnormal return (CAR) across T periods is defined as:

$$CAR_{jT} = \sum_{t=1}^{T} AR_{jt} \tag{2.2}$$

The abnormal return is $AR_{jt} = R_{jt} - R_{mt}$, where R_{jt} is the monthly return, R_{mt} is the contemporaneous return of the CFMRC value weighted index (with dividends), and CFMRC equal weighted index as well as normal return estimated by Fama-French three factor model are also used as robustness checks.

2.2.6 Buy-and-hold abnormal return

Firm j's buy-and-hold abnormal return (BHAR) across T periods is defined as:

$$BHAR_{jT} = \prod_{t=1}^{T}(1 + R_{jt}) - \prod_{t=1}^{T}(1 + R_{mt}) \tag{2.3}$$

2.2.7 Identify the how hot the IPO Market is with Markov-switching decomposition

In order to measure the hotness of the IPO market precisely, we follow the business cycle literature to analyze nonstationary time series Hamilton (1989) and the method further refined in Filardo (1994) to decompose IPO number series into trend part and cyclical part. Using cyclical part, I get a measure for the hotness of the IPO market. I assume the monthly numbers of IPO follow a time varying parameter (TVP) model with switching variance. Note that Markov-switching variance model alone fails to incorporate the time-varying nature of coefficients, TVP model alone fails to incorporate risk of changing of the heteroskedasticity of the disturbance term. If we put Markov-switching variance model and TVP model together, we can capture both the IPO numbers change in coefficients and disturbance variances. Therefore, we use the following general model as proposed in Filardo (1994) are used

$$\begin{aligned}
Y_t &= X_{t-1}\beta_t + e_t, \qquad t = 1, 2, \cdots, T \\
\beta_t &= \beta_{t-1} + v_t, \\
v_t &\sim N(0, Q) \\
e_t &\sim N(0, h_t) \\
h_t &= \sigma_0^2 + (\sigma_1^2 - \sigma_0^2)S_t
\end{aligned} \tag{2.4}$$

with

$$\Pr[S_t = 1|S_{t-1} = 1] = p_{11}, \quad \Pr[S_t = 0|S_{t-1} = 1] = 1 - p_{11}$$
$$\Pr[S_t = 1|S_{t-1} = 0] = 1 - p_{00}, \quad \Pr[S_t = 0|S_{t-1} = 0] = p_{00}$$

where Y_t is the monthly number of IPOs, X_{t-1} is the lagged one period monthly number of IPOs, S_t is states (hot or non-hot), ps are transition probabilities, v_t and e_t are error terms. Using Kalman's filter, we estimate the parameters and decompose the time series of IPO numbers into two parts, the trend, and the cycle. The cycle part is then standardized and used as a precise measure of the hotness of the IPO market.

2.3 Results

2.3.1 Long-run performance and IPO cycle measured with dichotomous method

For a sample of 1,005 Canadian IPOs from 1985 to 2010, 548 firms (54.6%) are issued in hot IPO cycle. In terms of both CAR and BHAR, in short term (around six month), IPO firms are underpriced and outperform the Canadian market, which is consistent with most previous literatures (e.g., Boabang, 2005; Jog & Wang, 2002). However, this result is derived from simple market index model. If we use more sophisticated techniques such as matching a firm's performance to its industry peers', as in Zheng (2007), the difference may become insignificant. In a longer horizon up to 4-years, IPO firms underperform the market return, which is consistent with previous findings that Canadian IPO firms underperform in the long-run (Kooli, L'Her, & Suret, 2006; Kooli & Suret, 2004).

My results show that the firms issued during hot IPO cycle underperform the firms issued in non-hot cycle in a 3 to 5-year horizon, which is drastically different from U.S. empirical result in Colak and Gunay (2011). Only after 6-years, firms issued during hot IPO cycle begin to outperform those issued in non-hot cycle. Fig. 2.3 shows buy-and-hold abnormal returns, cumulative abnormal returns graph shows the similar pattern but is abbreviated here to save space.

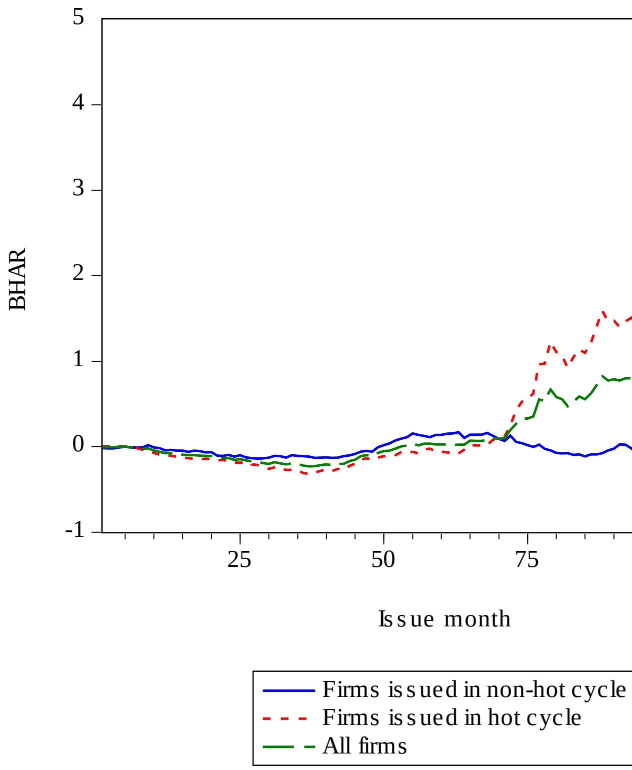


Figure 2.3: Average Buy-and-Hold Abnormal Return (BHAR) across Issue Month

This figure shows buy-and-hold abnormal returns of firms issued in non-hot cycle and the firms issued in hot cycle, we can see that at a horizon longer than 6 years, the performance difference is significant, and firms issued in hot cycle perform better. This provides support for prediction 1 of this paper, and subsequently provides support for strategic waiting theory. Cumulative abnormal returns graph shows the similar pattern but is abbreviated to save space. See page 18 for more discussion.

2.3.2 Long-run performance and IPO cycle measured with Markov-switching model

To study the relation between the quality of the firm and its timing to go public more precisely, I relate the performance of the firm in different horizons to the probability of being in hot IPO cycle when the firm goes public. Strategic waiting theory predicts a monotonic positive relationship, but I find an inverted U-shaped relation , i.e. low quality firms issue in extremes of IPO cycle (both in very low and very high possible that the IPO market is hot), and high quality firms issue in the middle of IPO cycle (during the possibility of being in hot IPO cycle is modest). I divide the IPO firms into 10 portfolios according to the probability of being in hot IPO cycle when going public, and then compute the in-group average of the probability of in hot IPO cycle and average 3-year, 6-year, 10-year CARs and BHARs.

In specific, in 3-year horizon, there is a negative linear relation between firm quality (stock performance) and the patience in strategic waiting (probability of being in hot IPO cycle). In 6-year horizon, the relation between firm quality and the patience in strategic waiting is inconclusive; there is no significant linear or non-linear relation. In 10-year horizon, there is a significant inverted U-shaped relation between firm quality and the patience in strategic waiting. Those relations can be identified by eyeballing Fig. 2.4. Fig. 2.4 visualized the relation between stock performance (both CAR and BHAR) and the probability of being in hot IPO cycle for 10-year horizon (graphs for 3-year and 6-year horizon are omitted to save space). Linear regressions on the firm quality and patience in waiting for 10 portfolios have same conclusions.

2.4 Robustness check

In order to check the robustness of the inverted U-shaped relation , pooled regressions on the relation between firm quality and its patience in strategic waiting, controlling

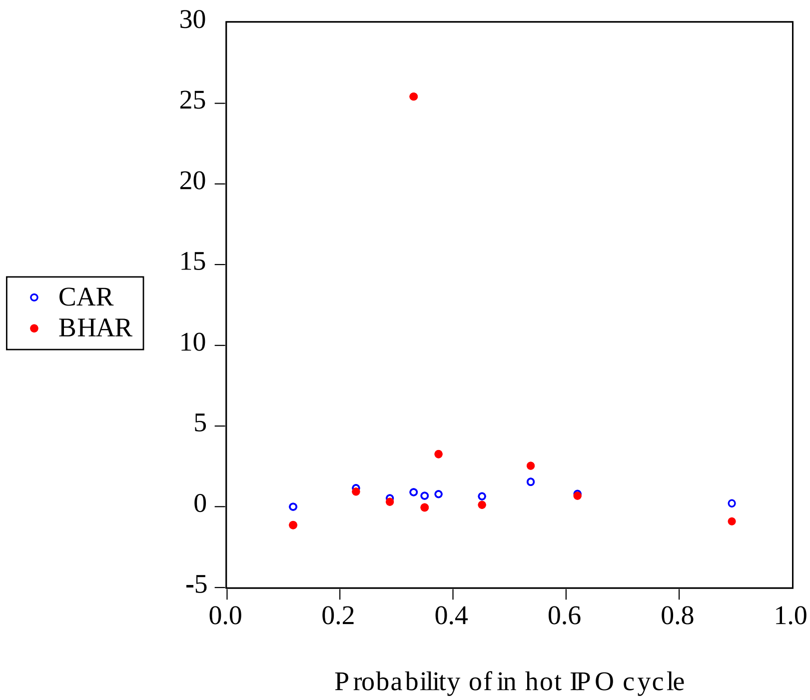


Figure 2.4: 10-year horizon firm performance and the probability of hot IPO cycle by portfolios

Long-run performance measure cumulative abnormal return (CAR) and buy-and-hold abnormal return (BHAR) are defined in equation (2.2) and (2.3). We divided the firms into 10 groups according to the hotness of IPO market when the firms went public. If the sample size is large enough, the within group noises would cancel out and for every group as a whole there would be a monotonic relation between the hotness of market when issuing and the long-run performance. In this graph we find that the relation is not monotonically increasing, but a U-shape curve. The complexity could be the result of multiple factors, for example, market timing attempts of firms will result in many low-quality firms be attracted by very hot market and decide to go public at the peak of market; another explanation is that strategic waiting theory itself needs extension to allow this non-linear relation.

for the industry effect, and allowing for both linear and second-order flexible non-linear relation are estimated on both CAR and BHAR for different horizons. Panel A of Table 2.2 reports the estimation results of firm's quality as measured in CAR and its patience in strategic waiting as measured in the probability of being in hot IPO cycle. For 3-year horizon, the negative linear relation is significant, and the coefficient for pr (probability of being in hot IPO cycle) is -0.432 with 5% level of confidence. For 6-year horizon, both linear and non-linear relations are not significant. For 10-year horizon, non-linear relation is significant, the coefficient for pr is 3.757 with 5% level of confidence, and the coefficient for pr^2 (pr-squred) is -3.295 with 5% level of confidence, which imply the firm's performance increase with firm's patience but at a decrease rate (i.e. an inverted U-shaped relation). Panel B of Table 2.2 reports the estimation results of firm's quality as measured in BHAR and its patience in strategic waiting as measured in the probability of being in hot IPO cycle. The results in panel B are similar with those in panel A, the only difference is that the significance level reduced to 90% for 10-year horizon.

2.5 Conclusion and discussion

Strategic waiting theory proposed in Colak and Gunay (2011) is supported by Canadian data in a longer horizon (6-year) compared with U.S. data, and in shorter horizons (3 to 5-year) the effect is not significant. Thus this "strategic waiting market anomaly" do exists in Canadian markets, but it needs longer time to appear. This implies country-specific factor may affect IPO decision in the strategic waiting process. There are at least two possible explanations for why Canadian markets need more time for this anomaly. First, Canadian capital markets could be simply not as efficient as U.S. capital markets are, for example, Canadian markets have a larger portion of penny stocks than U.S. markets because of lax listing and delisting requirements (Carpentier & Suret, 2011). Second, this difference could be the result of some measurement biases on

Table 2.2: Regression result of firm performances and the probabilities being in hot IPO cycle

The dependent variable is the firm's performance (as measure in CAR and BHAR) in different horizons (3-year, 6-year and 10-year). The independent variables are industry dummies (omitted because they are not our concern), "pr" stands for the probability of being in hot IPO cycle when going public, "pr2" is the pr squared, "N" is the number of observations, "R-sq" is R-squared. From coefficient "pr", we can see that in 3-year horizon, firms issued in non-hot IPO cycle outperform firms issued in hot IPO cycle, in 6-year horizon the performances are not statistically differ, in 10-year horizon the firms issued in hot IPO cycle (assumingly with higher percentage of high-quality firms) outperform firms issued in non-hot cycle. From coefficient "pr2", we can see that for 10-year horizon there is a statistically significant inverse U relation between probability of issued in hot cycle and long-run performance, which indicate we may need to extend strategic waiting theory or there are other factors in play (such as market timing). See page 20 for more discussion.

	3-year	Horizon	6-year	Horizon	10-year	Horizon
Panel A: firm performances as measured in CAR						
(Industry dummies omitted)						
pr	-0.432**	-0.853	-0.202	-0.243	0.192	3.757**
	(-2.300)	(-1.015)	(-0.603)	(-0.206)	(0.36)	(2.105)
pr2		0.391		0.038		-3.295**
		(0.544)		(0.038)		(-2.152)
Constant	0.06	0.166	1.025***	1.034***	0.377	-0.585
	(0.793)	(0.735)	(8.83)	(3.5)	(1.361)	(-1.071)
N	619	619	392	392	202	202
R-sq	0.03	0.03	0.076	0.029	0.06	0.079
Panel B: firm performances as measured in BHAR						
(Industry dummies omitted)						
pr	-0.704***	-1.445	-1.268	-1.13	-4.816	15.383*
	(-3.073)	(-0.977)	(-1.464)	(-0.327)	(-0.931)	-1.758
pr2		0.689		-0.127		-18.669*
		(0.567)		(-0.044)		(-1.762)
Constant	0.102	0.288	2.204***	2.171**	3.872	-1.582
	(1.111)	(0.723)	(7.337)	(2.499)	(1.443)	(-0.684)
N	619	619	392	392	202	202
R-sq	0.036	0.037	0.029	0.029	0.2	0.21

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

normal returns, for example, some literature show Fama-French three-factor pricing model is insufficient for Canadian stock market, and instead, a four-factor model should be used (L'Her, Masmoudi, & Suret, 2004).

The finding about the implications. It implies the strategic waiting theory itself may need to be extended to accommodate a non-linear relationship, and it may also imply the existence of an optimal patience level for high-quality IPO firms (when the first order condition equals zero).

The limitations of this study include but not limited to the following. First, this study is not free from survivorship bias. The significantly higher stock returns of firms issued in hot IPO cycles might be because many low quality firms were delisted in a 6-year period windows, and only high quality firms survived, and as the strategic waiting theory predicts, high quality firms are more likely to be issued in hot IPO cycles. Second, the influence of penny stocks is not excluded. I did not do a special treatment to exclude the penny stocks in my study. As a result, the stock returns might looks more volatile. However, I did use value weighted returns, which could partly alleviate this problem since penny stock firms typically are small firms. Third, outliers could influence the result. In Fig. 2.4, a group of firms issued at around 0.4 of IPO market hotness have an average of 25% BHAR, which is much higher than the second highest BHAR group which is about only 4%. It seems like an outliner. However, this is not the value of a single firm, but the average of value of more than one hundred firms, it should not be treated as an outlier. Even if we delete this group, the inverted-U shape still exists, as showed in the figure. Fourth, cross listed firms are not dealt with separately. The firms listed both in domestic and international markets are not treated separately. As a result, the difference between cross listed firms and non-cross listed firms are not shown in this study.

There are three future directions for further research in strategic waiting theory. First, it is interesting to test if strategic waiting exist in other international IPO markets, such as European and Asian markets. Second, ex-post IPO market hotness measure could be replaced by the ex-ante hotness measure by computing only with the historical data before each time point, instead of computing as a whole as in this paper. Third, it is necessary to test if the inverted U-shaped relation exists for the U.S. and other international markets. If the answer is “yes”, that would suggest the inverted U-shaped relation might be universal, and very likely strategic waiting model needs extension.

CHAPTER

THREE

DO STRATEGIC WAITING BEHAVIORS IN IPO MARKETS AFFECT FIRMS' SUBSEQUENT CAPITAL STRUCTURE DECISIONS?

This chapter investigate whether firms issued in hot IPO cycles, which supposedly with higher portion of high quality firms that strategically waited longer in IPO market than low quality firms do (Colak & Gunay, 2011), also differ in speed of adjustment (SOA) toward target debt ratios and in debt leverage levels. This chapter uses dynamic panel data with a system GMM estimator, and dynamic panel data with fractional dependent variable (DPF) estimator in a sample of 122,454 firm-year data from year 1965 to 2013. I find that the firms issued in hot IPO cycles on average have about 12%-260% relatively higher SOA depending on econometric model used, and have no significant difference in terms of leverage levels, however, for firms in different age groups, there is weak evidences consistent with strategic waiting theory.

3.1 Introduction

The strategic waiting theory (Colak & Gunay, 2011) argues that high quality firms wait more patiently for hot market signals than low quality firms do in initial public offerings (IPO). This chapter test wether these high quality firms also have different speed of adjustment (SOA) towards target ratios[1], and different leverage levels comparing with low quality firms, in subsequent capital structure decisions. If differences exist, then in turn they provide evidences supporting the strategic waiting theory from a capital structure decision perspective. In addition, this chapter also sheds new light on the relation between strategic waiting behaviors and firms' subsequent capital structure decisions, which has not been discussed before in the literature.

Using dynamic panel data (PDP) with system GMM estimator and PDP with a fractional dependent (DPF) variable estimator, with the 122,454 firm-year data from 1965 to 2013, I find evidences supporting such differences exist in SOA. Specifically, I find strong evidence that firms issued in hot IPO cycles have on average about 12%-260% relatively higher SOA, but there is no evidence that those firms also have different debt leverage levels. In other words, firms waited more patiently during IPO process, also have higher speeds in capital structure adjustment.

The empirical test is conducted under the framework of partial adjustment theory of capital structure, which itself is a development of trade-off theory. The empirical test employs recent development in econometric methods, the dynamic panel data with a system GMM estimator by Blundell and Bond (1998), and dynamic panel data with fractional dependent variable (DPF) estimator proposed by Elsas and Florysiak (2013).

This chapter is organized as follows: section 1 introduce the motivation and organization of this paper, section 2 provides literature review, section 3 discusses models to be estimated, section 4 provides a detailed description of the data, section 5 reports

[1]nevertheless, many literatures do not agree with the existence of target ratio, e.g. Graham & Harvey, 2001 and Baker & Wurgler, 2002; in this paper, I assume these targets exist, and test under this assumption whether the capital structure decision would be different.

estimation results, section 6 provides robustness check and section 7 concludes this paper.

3.2 Literature review

In this section, I discuss the strategic waiting theory of IPO firms, and the major capital structure theories, including static trade-off theory, partial-adjustment theory, as well as previous empirical estimation results of SOA and market timing theory.

3.2.1 Strategic waiting behavior in IPO market

Colak and Gunay (2011) developed a strategic waiting model for IPO firms. They assume there are two kinds of firms in the IPO market: high quality firms and low quality firms. Under information asymmetry, prior to IPO the investors do not know what types the firms belong to, but the managers of the firms know their own types. Suppose the fair price for a share of high quality firm is P_H, for a share of low quality firm is P_L. On average investors are willing to pay a price P for a share, where $P_L < P < P_H$. High quality firms are reluctant to sell their shares through IPO at discount, therefore they wait until the market is confirmed to be in a “hot issue" cycle when the investors are paying a premium for a share. Colak and Gunay showed that, under reasonable parameter assumptions, high quality firms have incentives and can afford the waiting, while low quality firms do not.

Colak and Gunay support their theory in three ways. First, a survival analysis is conducted to shows that highest quality decile firms have higher median waiting days than firms in the lowest decile. Second, firm quality is higher on the later part of an “hot issue" IPO cycle than that of firms issued in later part of the cycle. Third, S&P 500 firms, which are considered to be high quality firms, generally issue in confirmed hot issue cycle.

However, some doubts still exist about how robust the strategic waiting theory of

IPO firms is. One concern is about the first method used to test the strategic waiting theory, its underlying assumption is that all firms begin their IPO preparation process at the beginning of a hot issue cycle, which is very restrictive. In addition, empirical evidence from Canadian IPO data shows in a 5-year window, firms issued in non-hot IPO cycle outperform firms issued in hot IPO cycle, although in a longer time window (10 to 15-year) firms issued in hot cycle have better performances (Ma, 2012).

In order to provide an intuition to understand the strategic waiting theory of IPO firms, let us consider an analogy. In a dark forest, different animals are born at random points of time. Some born in the springs, some born in the summers. Colak and Gunay argue the animals born in the springs and animals born in the summers are different species, and the evidence is that those born in the summers are healthier than those born in the springs. If I could also show the animals born in summers are swifter than those born in the springs, then we can be more certain that they are indeed of different species. Similarly, if I could show that a firm's strategic waiting behavior, if exists, also have a consequence on the firm's capital structure decisions, then we will be more confident in the strategic waiting theory of IPO firms, this newly discovered relation may open doors for more interesting implications.

3.2.2 Theory of capital structure

The research in capital structure after the seminal work of Modigliani and Miller (1958) can be categorized into two groups. The first group recognizes the existence of an optimal level of debt (target leverage), while the second group does not.

The first group includes: trade-off theory (Baxter, 1967; Kraus & Litzenberger, 1973), which argues that a firm form an optimal leverage by balancing financial distress costs and tax savings benefits; agency theory (Jensen & Meckling, 1976; Myers, 1977), which argues a firm get an optimal leverage by minimizing stockholder-bondholder agency costs. and free cash flow theory (Jensen, 1986), argues a firm get an optimal

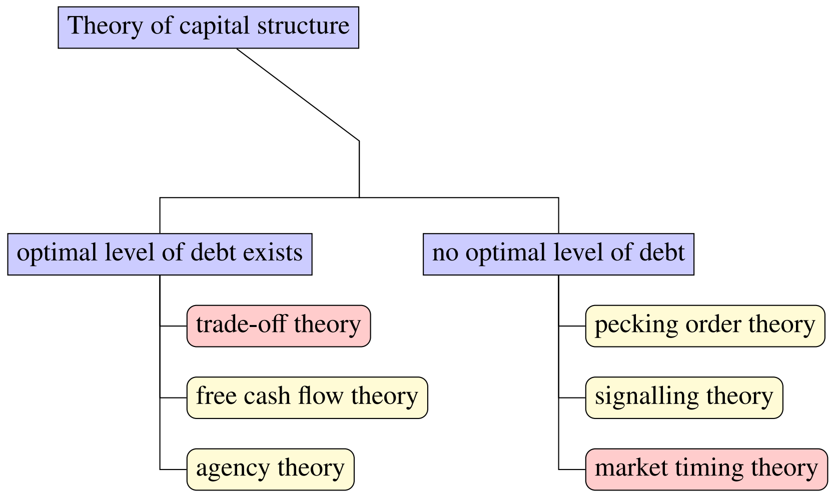


Figure 3.1: Major theories of capital structure

leverage by minimizing agency costs of free cash flow.

The second group rejects the idea of optimal leverage level, instead, it recognizes other determining factors. This group includes pecking order theory (Myers & Majluf, 1984b), which argues that a firm follows a financing hierarchy in order to minimize adverse selection costs of financing; market timing theory (Baker & Wurgler, 2002), which argues a firm chooses to issue equity or debt instruments, whichever is cheaper in financial markets at that point in time, to raise capital.

All of these theories have some supporting evidence as well as limitations, the current topic of debate is under what circumstance, with what firm characteristics, which theory would prevail (Graham & Leary, 2011). Fig. 3.1 shows the major theories of capital structure.

3.2.3 Static trade-off model

In order to understand the theoretical framework of the dynamic partial-adjustment model used for empirical test in this paper, it is necessary to go back to static trade-off model, which is the foundation for the partial-adjustment model.

Earlier research concentrates on the deterministic factors of a firm's capital structure, for example, Bradley, Jarrell, and Kim (1984), Titman and Wessels (1988) , Rajan and Zingales (1995), and Fama and French (2002). The underlying assumption of this line of research is that the observed leverage is the target leverage, and the adjustment cost is zero, thus the firm can instantly adjustment 100% towards its target when a divergence exists. In summary it is a static model:

$$L_{i,t+1} = L^*_{i,t+1} + \varepsilon_{i,t} = \mathbf{x}'_{i,t}\,\boldsymbol{\beta} + \varepsilon_{i,t} \tag{3.1}$$

where $L_{i,t+1}$ is the leverage for firm i in time $t+1$, $L^*_{i,t+1}$ is the theoretical optimal level, $\boldsymbol{\beta}$ is a coefficient vector, $\mathbf{x}_{i,t}$ is a vector of firm characteristics related to the costs and benefits of operating with various leverage ratios.

The stylized facts (see review papwers by Harris & Raviv, 1991; Frank & Goyal, 2008; Parsons & Titman, 2008) from static trade-off research includes firms size is positively related to leverage, asset tangibility is positively related to leverage, R&D intensiveness is negatively related to leverage, market-to-book ratio is negatively related to leverage, and high marginal tax rate firms are more likely to issue debt (Graham, 1996; Mackie-Mason, 1990).

Leverage ratios mean revert (Jalilvand & Harris, 1984) is consistent with the idea firms have a target leverage. Thus traditional trade-off predictions have empirical support.

However, static trade-off model also has many important shortcomings. First, profitability is negatively related to leverage which is inconsistent with the static trade-off model, because other things equal, more profitable firms should have higher tax-shield benefits (Graham, 2000). Second, much of capital structure variation remains unexplained by previously identified determinants (Lemmon et al., 2008).

3.2.4 Dynamic partial-adjustment model

The dynamic partial-adjustment model is the foundation for the empirical test in this paper, therefore it well worth more discussion. The partial-adjustment model is developed to address the shortcomings of the static trade-off model. We often want to keep a model as simple as possible, until it cannot make reasonably good predictions. In order to overcome the shortcomings of static trade-off model, the adjustment cost is added into the model, and such cost often prevents a firm from archiving optimal target ratio. That is, a firms' actual leverage may deviate from its optimal level for many reasons such as market timing behavior, and could not adjust back to optimal level because the adjustment costs outweigh the benefits. Under this new model, which is often called "partial-adjustment model" of capital structure, actual leverage is a poor proxy for optimal leverage, and it creates problems for static trade-off model estimation.

Partial-adjustment model is developed to address the poor proxy problem of static trade-off model due to adjustment costs. The basic idea is that if a firm actively adjust its leverage toward a target over time, we should observe evidence of leverage converging to target, i.e. a big γ in a commonly used empirical specification of partial-adjustment model (e.g., Flannery & Rangan, 2006):

$$L_{i,t+1} - L_{i,t} = \alpha_{i,t} + \gamma \left(L^*_{i,t+1} - L_{i,t}\right) + \epsilon_{i,t+1} \tag{3.2}$$

where $L^*_{i,t+1}$ is the optimal leverage level for firm i in time $t+1$, and γ measures the "speed of adjustment" (SOA), i.e. how much a firm closes the gap between its actual and its target leverage ratio each year. However, the unobservable target leverage $L^*_{i,t+1}$ must be specified and estimated, usually as a linear combination of observable leverage determinants:

$$L^*_{i,t+1} = \mathbf{x}'_{i,t}\,\boldsymbol{\beta} \tag{3.3}$$

Plug the $L^*_{i,t+1}$ in Eq. (3.3) back into Eq. (3.2), we get the empirical estimation model used in this paper:

$$L_{i,t+1} = \alpha_{i,t} + (1 - \gamma_{i,t})\, L_{i,t} + \gamma_{i,t}\, \mathbf{x}'_{i,t}\, \boldsymbol{\beta} + \epsilon_{i,t+1} \tag{3.4}$$

Note that if $\alpha_{i,t} = 0$ and $\gamma = 1$ this model reduces to Eq. (3.1).

3.2.5 Previous empirical results of SOA estimation

Estimating the SOA, i.e. the γ in Eq. (3.4), tests the joint hypotheses that the target leverages actually exist and that firms actively adjust toward their targets. The underlying assumption is that on average the firms are at the optimal level, the under leveraged firms and the over leveraged firms will cancel out. Under this assumption, a big enough γ is considered to be the key for the success of this joint hypotheses test, although many authors do not agree with this argument, for example, Shyam-Sunder and Myers (1999), Chang and Dasgupta (2009) and Iliev and Welch (2010). The empirical methods used to estimate SOA and their results are discussed below.

Ordinary least squares (OLS) method: Fama and French (2002) use OLS method and estimate the SOA to be between 9% to 18%, they call it a “glacial readjustment." Kayhan and Titman (2007) use OLS and estimate the the SOA to be around 10%. The OLS method suffers from, among other problems, the heteroskedasticity, and endogeneity issue, thus the OLS estimation is biased.

Fixed effect (FE) model: Flannery and Rangan (2006) argue that SOA could be up to 38% using FE model, Lemmon et al. (2008) find 39% with FE model, Huang and Ritter (2009) find 17% with FE model long differencing estimator. The FE method is immune from heteroskedasticity problem, but still has endogeneity issues and serial correlations.

The system GMM estimator for dynamic panel data models (DPD): Ma (2013) use the system GMM estimator for DPD model, estimates SOA to be -2%, and if industry dummies are added, 12%. DPD model system GMM estimator, which combines the advantages of fixed-effect and IV/GMM models, and fixes with-in group serial correlation (Blundell & Bond, 1998). However, it still suffers from another major problem with the partial adjustment model, as noted by many researchers (e.g., Chang & Dasgupta, 2009; Iliev & Welch, 2010; Elsas & Florysiak, 2013; Flannery & Hankins, 2013), the dependent variable, debt ratio $L_{i,t}$, is fractional value, i.e. bounded between 0 and 1. This fractional dependent variable problem will bias DPD system GMM estimators, similar to applying OLS on censored data will get biased estimation results.

Dynamic panel data with fractional dependent variable (DPF) estimator: Elsas and Florysiak (2013) estimate SOA to be 26% by considering the impact of fractional dependent variables.

Non-parametric method: Iliev and Welch (2010) estimate the SOA to be a slightly negative value by using a non-parametric method, which is consistent with Ma (2013) result.

3.2.6 Market timing theory and strategic waiting theory

Market timing theory rejects the idea of "optimal capital structure". Instead, it argues that a firm's capital structure is the aggregate result of "market timing" attempts in the past. When a firm facing the choice between debt financing and equity financing, the firm will choose whichever is cheaper according to market condition at that time (Lucas & McDonald, 1990; Korajczyk, Lucas, & McDonald, 1992). Baker and Wurgler (2002) show that market timing activities have a persistent effect on a firm's capital structure.

Consider a basic model by Miglo (2010), with two types of firm: type L and type H. Firms face identical projects which cost c and returns t. A type H firm generates cash flow I in addition to cash flow from project. The cost and return of the project is public information, but the type of firm is private information.

There are three implications from this basic model. First, business cycle is positively related to equity issuance. Suppose business cycle affects t only. When economy is bad, no firm issues equity. When economy is ok, only type L firms issues equity. When economy is booming, both types firms will issue equity. Empirical work generally support the positive relation between equity issues and business cycle (Choe, Masulis, & Nanda, 1993; Bayless & Chaplinsky, 1996; Baker & Wurgler, 2002). Second, from basic model, we can see that overvalued firms always issue equity, while undervalued firms issued equity only if the benefits of equity issuance outweigh costs of underpricing. Empirical evidences support the prediction that stock price performance is important for equity issue decisions (Rajan & Zingales, 1995; Kamath, 1997; Graham & Harvey, 2001; Baker & Wurgler, 2002).[2] Third, before equity issuances, firms have positive abnormal returns on average. That is because overvalued firm will issue equity anyway, but undervalued firm need above averagely strong signal to issue equity. Empirical evidences support this prediction (Loughran & Ritter, 1995; Goldstein et al., 2001).

Colak and Gunay (2011) not only distinguish firm quality and their abilities to “timing" the market, but also assume the information asymmetry on market condition. In their model, the true market condition is unknown, all firms could only guess based on the IPO activities observed. In this sense, strategic waiting theory is a development of market timing theory.

3.3 Data

In this section, I discuss the source of fundamental data, the source of IPO data and how I identify hot IPO cycles.

[2]Some research argue that market timing is based on the market performance prior to the issue (“pseudo-market timing") instead of market performance (Schultz, 2003; Butler, Grullon, & Weston, 2005).

3.3.1 Fundamental data

Fundamental data containing firm characteristics measures of North America firms from year 1965 to 2012 is obtained from Compustat North America annual database. Following previous literatures (e.g., Fama & French, 2002; Flannery & Rangan, 2006), financial firms (SIC code 6000-6999) and utilities (SIC codes 4900-4999) are excluded from the sample. Financial and utilities firms are excluded because their capital structures are mainly determined by government regulations. All the dollar amount values are inflation adjusted using consumer price index, retrieved on October 16, 2013 from U.S. Department of Labor, Bureau of Labor Statistics (Labor, 2013). Following Fama and French (1997), firms are classified into 48 industries. To avoid the impact of outliers, all variables are winsorized at 1% level. Following Frank and Goyal (2003), financial deficit variable FINDEF is constructed. When constructing FINDEF, to minimize loss of information, the missing values of intermediate variables are set to zero. Table 3.1 reports summary statistics for important variables.

3.3.2 IPO data

I extract all the IPOs between 1970 and 2010 from the Securities Data Company (SDC) database. Following Colak and Gunay (2011), I apply the following selection criteria to construct the sample of initial public offerings (IPOs). Eliminate REITs, closed-end funds, ADRs, unit offers, and MLPs. After merging the SDC data with Computstat data, there are 8,158 distinct IPO events and 92,361 firm-year observations. Fig. 3.2 shows the IPO activities over time. This figures show the quarterly number of IPOs captured by SDC. The dark black line is the IPO numbers, the lighter red line is the four-quarter moving average, MA(4), the shaded bars indicates the U.S. economy recessions as defined by NBER. The timespan is between 1970 and 2010. The IPOs are only include the firms both in SDC and COMPUSTAT annual data base.

Table 3.1: Summary statistics of variables used in this paper

	Obs.	Mean	Median	Std. Dev.	Min.	Max.
BDR	191581	0.308	0.244	0.287	0	0.999
SPE	134403	0.00200	0	0.0830	-0.932	0.874
MDR	191581	0.442	0.327	0.379	0	0.999
EBIT_TA	165988	0.114	0.107	0.0940	-0.167	0.421
MB	142996	1.331	0.996	1.053	0.294	6.596
DEP_TA	172400	0.0430	0.0370	0.0270	0.00200	0.151
LnTA	173579	14.11	13.95	2.016	9.959	19.21
FA_TA	173278	0.340	0.290	0.231	0.00800	0.919
R&D_DUM	191581	0.417	0	0.493	0	1
R&D_TA	173579	0.0170	0	0.0420	0	2.970
Rated	191581	0.341	0	0.474	0	1
Ind_Median	191581	0.233	0.223	0.135	0	0.812
MB_EFWA	176487	2.495	1.882	2.559	0	9.999
L3MDR	113522	0.254	0.211	0.212	0	0.816
FINDEF	150597	0.0110	-0.00200	0.136	-0.400	0.539
IPO	191581	0.0250	0.0110	0.0250	0	0.0860

Source: Compustat North America annual database, 1965-2013, IPO data is from Bloomberg.

3.3.3 Identifying hot IPO cycles

The strategic waiting theory of IPO firms primarily about the issuing behavior of firms when the IPO market is hot, that is, the period IPO cycle is rising. Thus, the first step is to identify the rising IPO cycles.

The market heat is measured by the number of IPOs in each quarter. Then I take the 4-period moving average, MA(4), of the quarterly IPO issuance observations. The hot IPO cycle is defined as the MA(4) has risen for at least three back-to-back quarters. According to this definition, there are 13 hot cycles. After eliminating the hot cycle that is too below average IPO numbers, the 75/4-77/2; the cycle that is too short, 90/1-90/2; the cycle that involves too much turbulence, 07/2-07/4. There are 10 hot cycles identified: 71/3-72/4, 78/4-81/4, 83/2-84/1, 85/4-87/1, 91/2-92/3, 93/3-94/2, 95/4-96/4, 99/3-00/1, 04/1-05/1, and 09/4-10/4. The earlier part and the later part of hot cycle are also distinguished, if there are odd number of quarters n for a hot cycle, then the first

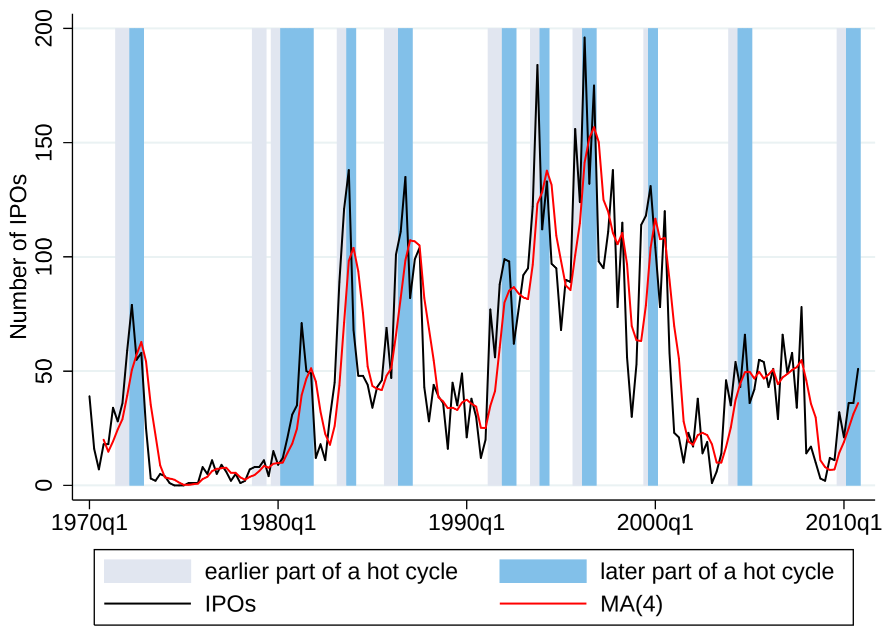


Figure 3.2: IPO activities over time (quarterly) with confirmed hot cycles

This figure shows the quarterly number of IPOs. The solid black line is the IPO numbers, the red (gray) line is the four-quarter moving average, MA(4), the shaded bars indicate the hot IPO cycles, and the darker part of the shaded bars indicate the later part of hot IPO cycles.

$(n-1)/2$ quarters are classified as earlier part, and the remaining $(n+1)/2$ quarters are later part. See Fig. 3.2.

3.3.4 Multicollinearity diagnostics of explanatory variables

In this section, I will show my regression results are free from multicollinearity problem. Multicollinearity exists when there is a perfect or close relation between the explanatory variables. In this case, matrix $(\mathbf{X}'\mathbf{X})$ will not be invertible, or the $(\mathbf{X}'\mathbf{X})^{-1}$ will be "large". Under multicollinearity, the estimated coefficients will still be unbiased, i.e. $E[\hat{\beta}_k] = \beta_k$. However the confidence intervals will be inflated. In addition, the estimation results will be very sensitive to changes in specification of the model,

Table 3.2: Collinearity Diagnostics

Variable	VIF	SQRT_VIF	Tolerance	R-Squared
MDR	1.99	1.41	0.5021	0.4979
FNM_MDR	1.51	1.23	0.6623	0.3377
EBIT_TA	1.41	1.19	0.7102	0.2898
MB	1.59	1.26	0.6307	0.3693
DEP_TA	1.55	1.25	0.644	0.356
LnTA	1.08	1.04	0.9228	0.0772
FA_TA	1.76	1.33	0.5685	0.4315
RnD_DUM	1.36	1.16	0.7373	0.2627
RnD_TA	1.57	1.25	0.6365	0.3635
Ind_Median	1.65	1.28	0.6059	0.3941
IPO	1.3	1.14	0.7694	0.2306
Mean VIF	1.52			

dropping a variable or excluding some observations may drastically change the estimated coefficients. The biggest problem of multicollinearity is that the explanatory effects of individual explanatory variables cannot be separated.

I will use Variance Inflation Factor (VIF) to detect multicollinearity problem.

$$\text{tolerance} = 1 - R_k^2, \quad \text{VIF} = \frac{1}{\text{tolerance}}, \tag{3.5}$$

where R_k is the goodness of fit using kth explanatory variable as the new variable being explained, and use remaining independent variables $\{x_1, x_2, \ldots x_{k-1}, x_{k+1}, \ldots, x_K\}$ as explanatory variables for x_k. Table 3.2 reports the VIF values of explanatory variables. A rule of thumb is that if VIF is less than 4, we do not need to worry about multicollinearity issue. Here we have all VIF values smaller than 2, therefore the multicollinearity is not a problem for my regression here.

3.4 Estimation

In this section, I discuss the two proxies for leverage ratio: the market debt ratio (MDR) and book debt ratio (BDR); the firm characteristic variables used to estimate the target leverage; the equity market condition index to alleviate no year dummy in DPF estimation; the regression models; and model estimation techniques involved, including OLS, fixed effect, dynamic panel data with system GMM estimator, and dynamic panel fractional estimator.

3.4.1 Variables

Following Flannery and Rangan (2006), I specify the variables to be estimated, including the debt leverage measure $L_{i,t}$, the target debt leverage $L^*_{i,t}$, and firm characteristics $\mathbf{x}_{i,t-1}$ used to estimate target debt leverage $L^*_{i,t}$.

Debt leverage measure: market debt ratio

Primary embodiment of debt leverage measure is a firm's "market debt ratio".

$$MDR_{i,t} = \frac{D_{i,t}}{D_{i,t} + S_{i,t} P_{i,t}} \tag{3.6}$$

where $MDR_{i,t}$ is debt of firm i at period t divided by the sum of debt and firm market value; $D_{i,t}$ is the debt of firm i at period t (Compustat variable DLC plus DLTT); $S_{i,t}$ is the number of common shares outstanding (Compustat variable CSHO); $P_{i,t}$ is the price per share of firm i at period t (Compustat variable PRCC_F).

Debt leverage measure: book debt ratio

For robustness check, the secondary embodiment of debt leverage measure is a firm's "book debt ratio":

$$BDR_{i,t} = \frac{D_{i,t}}{TA_{i,t}} \tag{3.7}$$

where $D_{i,t}$ is the sum of long-term debt (Compustat variable DLC) and short-term debt (Compustat variable DLTT); $TA_{i,t}$ is total asset of firm i at period t (Compustat variable AT).

Target leverage

The "target leverage ratio" is unobservable. For example, a survey conducted by Graham and Harvey (2001) shows that most CFOs do not have target leverages in mind; it's theoretically estimation is defined as

$$L^*_{i,t} = \mathbf{x}'_{i,t}\,\boldsymbol{\beta} \tag{3.8}$$

where $L^*_{i,t}$ is the target leverage ratio; $\boldsymbol{\beta}$ is a coefficient vector; $\mathbf{x}_{i,t-1}$ is a vector of firm characteristics related to the costs and benefits of operating with various leverage ratios.

Firm characteristic variables $\mathbf{x}_{i,t}$

Following Flannery and Rangan (2006), the following firm characteristics are used to estimate the target leverage ratio $L^*_{i,t}$. EBIT_TA: earnings before interest and taxes (Compustat variable EBIT) as a proportion of total assets (Compustat variable AT); MB: market to book ratio of assets, i.e. book liabilities plus market value of equity (Compustat variables DLTT + DLC + PSTKL + PRCC_F×CSHO) divided by book value of total assets (Compustat variable AT); DEP_TA: depreciation expense as a proportion of total assets (Compustat variables DP/AT); LnTA: natural log of total assets (Compustat variable $\ln(TA)$); FA_TA: fixed assets as a proportion of total assets (Compustat variables PPENT/AT); R&D_DUM: dummy variable indicating that the firm did not report R&D expenses (Compustat variable XRD); R&D_TA: R&D expenses as a proportion of total assets (Compustat variable XRD/AT); Ind_Median: median debt ratio of firm i's Fama and French (2002) industry classification at time t; and Rated: dummy variable equals one if the firm has a public debt rating in Compustat, zero otherwise (Compustat variable SPCSRC).

Equity market condition index

The target leverage ratio may not be determined by firm characteristics only, the equity market condition, on the other hand, may also play a role in a firm's optimal leverage level determination. That is, if the equity market condition is good, there should be a higher premium for the equity, as a result a firm may have a lower optimal leverage ratio.

Due to the construction of DPF estimator, year dummies cannot be included when estimating DPF model in the later part of this paper. In order to partly alleviate the problem, I use equity market condition index in the estimation. To measure the equity market condition, I use the IPO data for North America firms from year 1965 to 2012 which is retrieved from Bloomberg. I exclude financial and utilities industries. I use Bloomberg instead of SDC because Bloomberg captures more IPOs. For example, from 1971 to 1999, there are 2,200 IPOs in SDC (Alti, 2006) compared with 5,812 IPOs from Bloomberg in my paper.

Table 3.3 reports the summary statistics of IPO data. There are 48 years of observations; the mean IPO size is $14.08 billion US dollars; annual average number of IPOs is 191.29; market size increased from $440.06 billion in year 1965 to $20.30 trillion in year 2012, with an average of $6.72 trillion; number of public firms is calculated using Compustat North America fundamentals annual number of firms excluding finance and utilities industries; relative IPO size is calculated as size of IPO divided by market size (again, excluding financial and utilities industries, firms in Compustat North America fundamentals annual only) and its average is 0.15%; relative IPO number is calculated as numbers of IPO divided by number of public firms (in Compustat North America fundamentals annual database, excluding financial and utilities industries) and is average is 4.65%.

Figure 3.3 shows the number of IPOs and size of IPOs over time. Note that IPO size is not inflation adjusted, and numbers of IPO are not adjusted according to the numbers

Table 3.3: IPO activities from 1965 to 2012 captured by Bloomberg

	Obs.	Mean	Std. Dev.	Min	Max
IPO size (million \$)	48	14081.82	17062.04	0.50	58156.60
Number of IPOs	48	191.29	214.70	1	891
Market size (million \$)	48	6721897.00	7140816.00	431327.00	21542062
Number of Public firms	48	3991.27	760.16	2439.00	5322.00
Relative IPO size	48	0.0015	0.0015	0.0000	0.0050
Relative IPO number	48	0.0465	0.0473	0.0002	0.1674

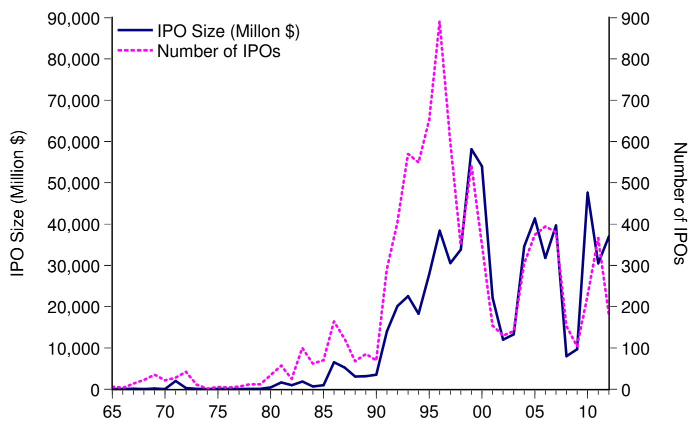


Figure 3.3: IPO sizes and numbers

of existing public firms as in Alti (2006). As a result, they are not good measures of how hot the IPO market is.

Figure 3.4 show the relative IPO size and relative number of IPOs over time. Since IPO size is adjusted by market size, number of IPOs is adjusted by existing number of public firms, these relative measures are more appropriate. I construct an equity market conditio index out of the relative IPO size and relative numbers of IPO:

$$\text{Equity market conditio index} = \frac{1}{2} \times \left(\frac{\text{Relative IPO size}}{mean(\text{Relative IPO size})} + \frac{\text{Relative IPO number}}{mean(\text{Relative IPO number})} \right) \tag{3.9}$$

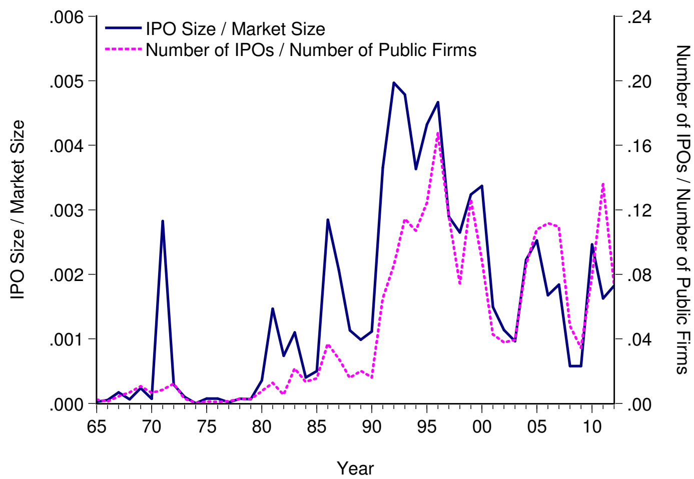


Figure 3.4: Relative IPO sizes and numbers

From Table 3.6, we can see that the equity market condition index is significant at 99% level in fixed effect model and IV model, which implies it may be necessary to add it into optimal leverage determination model.

3.4.2 Regression model

Following Flannery and Rangan (2006), the standard partial-adjustment model is

$$L_{i,t} - L_{i,t-1} = \alpha_{i,t} + \gamma \left(L^*_{i,t} - L_{i,t-1}\right) + \epsilon_{i,t} \tag{3.10}$$

Plug in Eq. (3.8) and rearrange the Eq. (3.10):

$$L_{i,t} = \alpha_{i,t} + \gamma\, \mathbf{x}'_{i,t}\, \boldsymbol{\beta} + (1-\gamma)L_{i,t-1} + \epsilon_{i,t} \tag{3.11}$$

By using $MDR_{i,t}$ as the proxy for leverage $L_{i,t}$, we have

$$MDR_{i,t} = \alpha_{i,t} + \gamma\, \mathbf{x}'_{i,t}\, \boldsymbol{\beta} + (1-\gamma)MDR_{i,t-1} + \epsilon_{i,t} \tag{3.12}$$

Eq. (3.12) is the empirical estimation equation we mainly use in this paper.

3.4.3 Model estimation techniques

In this section, I review the previous methods of model estimation. An important issue when conceiving a model is how to deal with unobservable $L^*_{i,t}$.

Previous estimation techniques

Various estimation techniques have been used to estimate the partial-adjustment model as specified in Eq. (3.12). From ordinary least square to fixed effect model.

In many research papers, simple OLS is used to estimate the debt leverage ratio (e.g., Hovakimian, Opler, & Titman, 2001; Fama & French, 2002; Korajczyk & Levy, 2003; Kayhan & Titman, 2004). The estimation model is specified as

$$L_{i,t+1} = \alpha + \mathbf{x}'_{i,t}\, \boldsymbol{\beta} + \epsilon_{i,t+1} \tag{3.13}$$

Some researches apply OLS directly to Eq. (3.12). The estimation model is specified as

$$L_{i,t+1} = \alpha + \gamma\, \mathbf{x}'_{i,t}\, \boldsymbol{\beta} + (1-\gamma) L_{i,t} + \epsilon_{i,t+1} \tag{3.14}$$

Fixed effect model (e.g., Flannery & Rangan, 2006) can deal with omitted variable problem, it is specified as

$$L_{i,t+1} = \alpha + \gamma\, \mathbf{x}'_{i,t}\, \boldsymbol{\beta} + (1-\gamma) L_{i,t} + v_i + \epsilon_{i,t+1} \tag{3.15}$$

There are alternative method to estimate the target debt ratios (TDR). TDR method uses OLS in Eq. (3.13) to estimate target debt ratio, in specific

$$L_{i,t+1} = \alpha + \gamma\, (TDR^{OLS}_{i,t}) + (1-\gamma) L_{i,t} + \epsilon_{i,t+1} \tag{3.16}$$

Three-year's lagging $L_{i,t}$ could also be used,

$$L_{i,t+1} = \alpha + \gamma\, \beta\, L_{i,t-3} + (1-\gamma) L_{i,t} + \epsilon_{i,t+1} \tag{3.17}$$

Dynamic panel date with system GMM estimator

The panel data estimation method can address individual effect of firms, however, it cannot address the endogeneity issue, i.e. the explanatory variable are correlated with the error term. When the explanatory variables include the lagged variable being explained, we call it is a dynamic panel data (DPD), in this case the FE estimator is biased because of “dynamic panel bias" or Nickell (1981) bias.

There are serval ways to estimate DPD model. One method is do first difference, but $\Delta y_{i,t-1}$ is correlated with $\Delta\epsilon_{i,t}$, Anderson and Hsiao (1981) use $y_{i,t-2}$ as instrument for $\Delta y_{i,t-1}$, which is called “Anderson-Hsiao estimator". Arellano and Bond (1991) use higher order lagged variable $\{y_{i,t-3}, y_{i,t-4}, \ldots\}$ as IV to do GMM estimation, which improved the estimation efficient, this is so called “Arellano-Bond estimator", also called “difference GMM".

The problem of difference GMM is that time invariable variables, such as gender, are eliminated. In our case, the variable of interest, the dummy variable indicating if the firm issue in hot IPO cycle, is eliminated. When the dependent variables $\{y_{i,t}\}$ follow a random walk process, the correlation between $y_{i,t-2}$ and $\Delta y_{i,t-1}$ is weak, which will cause weak instrument problem. To deal with these problems, Arellano and Bover (1995) return to the the level equation, and use $\{\Delta y_{i,t-1}, \Delta y_{i,t-2}, \ldots\}$ as IV for $y_{i,t-1}$, then do GMM estimation, this is called “level GMM".

Blundell and Bond (1998) combine the difference GMM and level GMM, estimate the difference equation and level equation as a system of equations, this is called “system GMM". System GMM can improve the estimation efficiency, and can estimate the coefficients for time invariable variables.

Dynamic panel fractional estimator

Elsas and Florysiak (2013) proposed the dynamic panel fractional (DPF) estimation for applications in panel regressions with a lagged fractional dependent variable. The reason we need DPF estimation is that the dependent variable is fractional and censored, i.e. bounded between zero and one. GMM estimators like Blundell and Bond (1998) will be biased.

The DPF estimator uses a doubly-censored Tobit specification with corner observations at 0 and 1, with a lagged dependent variable. DPF estimator employs a latent variable specification and estimates the regression equation

$$L^{\#}_{i,t+1} = \mathbf{x}'_{i,t}\,\boldsymbol{\beta} + (1-\lambda)L_{i,t} + c_i + \epsilon_{i,t} \tag{3.18}$$

where

$$L^{\#}_{i,t} = \begin{cases} 0 & \text{if } L_{i,t} < 0 \\ L_{i,t} & \text{if } 0 < L_{i,t} < 1 \\ 1 & \text{if } L_{i,t} > 1 \end{cases} \tag{3.19}$$

Loudermilk (2007) shows that in non-linear panel models there is no known transformation to eliminate unobserved fixed-effects (heterogeneity), therefore Elsas and Florysiak's DPF estimator specifies a conditional distribution for unobserved heterogeneity c_i as suggested by Loudermilk (2007). The unobserved fixed-effects distribution is assumed to be

$$c_i = \alpha_0 + \alpha_1 L_{i,0} + \bar{\mathbf{x}}'_{i,t}\,\boldsymbol{\alpha}_2 + \varepsilon_i \tag{3.20}$$

where $L_{i,t}$ is observable dependent variable, $\mathbf{x}_{i,t}$ is a set of exogenous regressors, $\epsilon_{i,t}$ is error term which follows $N(0, \sigma_u^2)$, $\bar{\mathbf{x}}_{i,t}$ is time series averages of $\mathbf{x}_{i,t}$, ε_i is error term follows $N(0, \sigma_\varepsilon^2)$, $i = 1, \ldots, N$, $t = 1, \ldots, T$. Elsas and Florysiak demonstrate with simulated data that the DPF estimator is unbiased when dealing with censored data, while other estimators such as OLS, FE, Fama-MacBeth, Blundell and Bond, LD, LSDVC are all biased.

3.4.4 Estimation results on difference in debt leverage

The core of strategic waiting theory of IPO firms is “reluctant to sell”, i.e., when a firm feels its value is underestimated, it is unwilling to sell its equity. The implication is that we expect to see that, for a newly issued high quality firm, when its true value is underestimated, it will have a higher debt ratio, only as time goes by, after its true value was revealed to market, its debt leverage will decrease.

For the whole sample, I did not find any evidence showing differences exist in terms of debt leverage levels for all the firms and firms issued in hot IPO cycles.

For firms in different age groups, I expect to see younger firms issued in hot IPO cycles have higher debt ratios, not only than older firms issued in hot IPO cycles, but also than younger firms issued in non-hot IPO cycles.

Difference in debt leverage for all firms

In this section, I test whether or not strategic waiting behavior influence a firm’s leverage ratio. To do this, I use dummy variables “hot” and “Later” to indicate whether a firm issued in hot IPO cycle and later part of a hot IPO cycle, and put the dummy variables into left hand of regression equations. The estimation methods need to accommodate such time invariant dummy variables, in specific, OLS, Fama and MacBeth, system GMM estimator, system GMM estimator with industry dummies. DPF estimator will also be used, but the mean values of the dummy explanatory variables will be deleted to avoid perfect collinearity, which in turn will make the estimation result theoretically inappropriate. If the coefficient before the dummy variable is positive, then it tends to increase the debt leverage ratio.

From Table 3.4, the result is inconclusive, there is no obvious pattern for the co-

Table 3.4: Regression results for all samples adding "hot" and "Later" dummies

This table summarizes the estimation results of: (1) FM, (2) OLS, (3) system GMM estimator, (4) system GMM with industry dummies, (5) DPF estimator. See page 48 for more discussion.

	(1) FM	(2) OLS	(3) SYS_GMM	(4) SYS_GMM_IND	(5) DPF_ALL
MDR	0.869***	0.865***	1.000***	0.569***	0.749***
	(70.75)	(231.94)	(55.33)	(18.56)	(111.58)
EBIT_TA	-0.035	-0.005	0.324***	0.202***	0.019*
	(-1.58)	(-0.58)	(18.10)	(11.35)	(1.77)
MB	-0.002**	-0.004***	0.021***	0.012***	0.003***
	(-2.02)	(-5.83)	(15.27)	(9.69)	(3.20)
DEP_TA	-0.275***	-0.286***	0.340***	0.203**	-0.535***
	(-6.33)	(-10.58)	(3.22)	(2.26)	(-9.10)
LnTA	-0.000	0.000	-0.018***	0.015***	0.009***
	(-0.40)	(0.95)	(-4.11)	(2.63)	(8.25)
FA_TA	0.032***	0.036***	-0.010	0.042*	0.088***
	(4.33)	(9.83)	(-0.39)	(1.79)	(8.59)
RnD_DUM	-0.002	-0.003**	-0.007	-0.005	0.009**
	(-1.26)	(-2.03)	(-1.06)	(-0.88)	(2.46)
RnD_TA	-0.155***	-0.161***	0.261***	0.226***	-0.006
	(-4.14)	(-9.20)	(3.97)	(4.16)	(-0.13)
Ind_Median	0.051***	0.040***	-0.270***	-0.148***	-0.039***
	(3.87)	(6.11)	(-10.13)	(-5.99)	(-3.00)
IPO	0.000	-0.007*	0.022***	0.061***	0.002**
	.	(-1.78)	(3.40)	(6.74)	(2.01)
con_hot	-0.002	-0.002	0.383***	-2.345	0.002
	(-0.68)	(-1.13)	(8.49)	(-0.33)	(0.51)
con_later	0.003	0.002	-0.130**	5.174	0.000
	(1.21)	(1.22)	(-2.00)	(0.69)	(0.10)
N	30588	30588	30588	30508	30588
N_group			4095	4085	4095
r2	0.770	0.774			
pseudo_R2	0.994	0.965	0.483	0.004	0.951
ar1					
ar1p					
ar2			-1.553	.	
ar2p			0.121	.	
sargan			692.735	.	
sargan_p			0.000	.	
speed	0.131	0.135	0.000	0.431	0.251
Half_Life	5.283	5.143	4584.026	1.608	2.767

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)

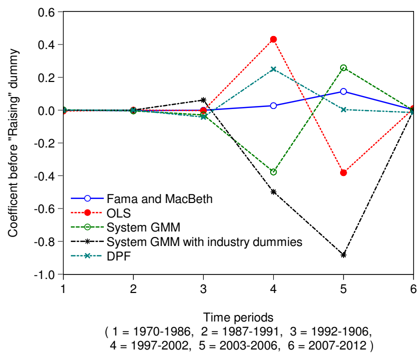
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

efficients of dummy variables. FM, OLS and DPF estimations report the coefficients not significantly different from zero. Only system GMM estimator reports a significant positive coefficient, but once industry dummies added in, the significance disappears.

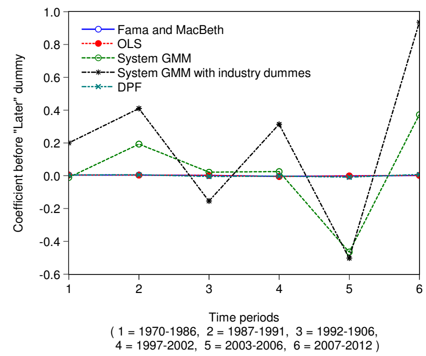
Next, I run the estimations over six time periods. The division of these time periods is discussed in more detail in page 66. To save space, the regression results are omitted, but the major findings are summarized in Fig. 3.5. Each figure represents regression results of five equations in six time periods, therefore thirty regression results in total. In specific, Fig. 3.5 summarizes estimation results for Fama and MacBeth, OLS, system GMM estimator, system GMM with industry dummies, and DPF estimator. Fig. 3.5a shows the coefficient of "hot" dummy, when both the "hot" and "Later" dummies are included in the regressions. Fig. 3.5b shows the coefficient of "Later" dummy, when both dummies are included in the regressions. Fig. 3.5c shows the coefficient of "hot" dummy, when 'hot" is the only dummy included in the regressions. Fig. 3.5d shows the coefficient of "Later" dummy, when 'Later" is the only dummy included in the regressions. I find no obvious pattern or trend for the coefficients. Again, FM, OLS and DPF estimators reports the coefficients not significantly different from zero; system GMM estimator reports a significant coefficient, but once industry dummies added in, the sign changes.

Difference in debt leverage for firm in different age groups

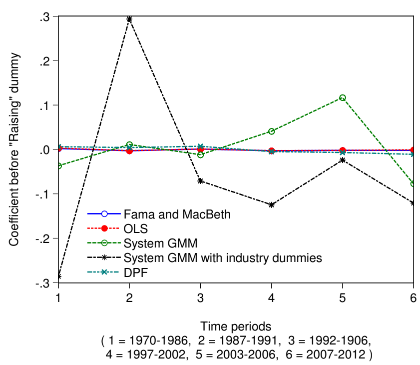
From the empirical results, on average I find no evidence that the debt leverages are different for firms issued in different phases of IPO cycles. However, difference may exists for firms within same age groups. The reason is as follows. The debt leverage maybe connected with a firm's age, it is important to compare the SOA of firms issued hot cycle and firms issued in non-hot cycle within a same age group. The basic idea of strategic waiting theory is that the managers of a high quality firm know their firm's true value, which is higher than average firms, as a result they refuse to sell the equity



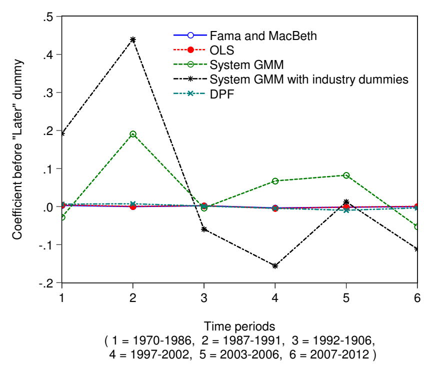
(a) Coefficient of “hot” with both dummies



(b) Coefficient of “Later” with both dummies



(c) Coefficient of “hot” with only one dummy



(d) Coefficient of “Later” with only one dummy

Figure 3.5: Coefficients of “hot” and “Later” dummies over 6 time periods

This figure summarizes estimation results for Fama and MacBeth, OLS, system GMM estimator, system GMM with industry dummies, and DPF estimator. Fig. 3.5a shows the coefficient of “hot” dummy, when both the “hot” and “Later” dummies are included in the regressions. Fig. 3.5b shows the coefficient of “Later” dummy, when both dummies are included in the regressions. Fig. 3.5c shows the coefficient of “hot” dummy, when ‘hot” is the only dummy included in the regressions. Fig. 3.5d shows the coefficient of “Later” dummy, when ‘Later” is the only dummy included in the regressions. See page 48 for more discussion.

cheap, instead, they wait until hot market when investors are paying a premium for the stock. The implication is that when the market did not know the true value of the firm, the management from high quality firms would prefer debt financing. As time goes by, after the true value of the firm has been revealed, the high quality firm will shift towards equity financing. If this is the case, we should observe high quality firms have higher debt leverages when young, and lower debt leverages when getting old. Since the issuance dates of high quality firms are more densely distributed in hot IPO cycles, we should observe the firms issued in hot IPO cycles have lower debt leverages when young, higher leverages when old.

To test this implication, different ages groups of firms are created and the coefficients before the dummy variable indicating a firms is issued in hot IPO cycle are compared. Table 3.5 reports the estimation results for Fama and MacBeth two step procedure, ordinary least squares model, system GMM with year dummy, system GMM with year and industry dummies, DPF estimator. We can see that every model expect system GMM with both dummies shows that for firms with age 3, 5 and 7 on average firms issued in hot IPO cycle have a trend to increase its debt leverage over time, which is consistent with strategic waiting theory's prediction. This finding is consistent with Leland and Pyle (1977). Leland and Pyle show that good firms can send creditable signals to the market by retaining a large fraction of the firm's equity. However, this trend is not statistically significant, and does not last beyond 7 years.

3.4.5 Estimation results on difference in SOA

In this section, I present the estimation results from OLS, FE, DPD system GMM, and DPF estimators.

Table 3.5: Coefficients before hot issue dummy for different age groups

This table presents different estimation results for Eq. (3.12) using (1) Fama and MacBeth two step procedure, (2) ordinary least squares model , (3) system GMM with year dummy, (4) system GMM with year and industry dummies, (5) DPF estimator. See page 50 for more discussion.

	FM	OLS	SYS_GMM_YR	SYS_GMM_YR_IND	DPF
Age < 3					
	-0.005	-0.004	-0.055**	0.461	0.003
	(-1.27)	(-1.31)	(-2.00)	(0.18)	(0.69)
Age < 5					
	-0.000	-0.000	0.141***	-1.185	0.005
	(-0.11)	(-0.16)	(5.04)	(-0.72)	(1.43)
Age < 7					
	0.000	-0.001	0.224***	0.156	0.006*
	(0.16)	(-0.72)	(8.90)	(0.14)	(1.90)
Age 7-15					
	0.003	0.001	0.108***	0.080	0.003
	(0.96)	(0.30)	(3.69)	(0.08)	(1.08)
Age 15-21					
	0.001	-0.001	-0.043	1.071	-0.006
	(0.21)	(-0.26)	(-1.25)	(0.41)	(-1.34)
Age > 7					
	0.003	0.002	0.133***	-0.940	0.001
	(1.08)	(1.08)	(3.87)	(-0.38)	(0.28)

t statistics in parentheses

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Preliminary estimation results on SOA

I start the empirical estimation by first reproduce key results of Flannery and Rangan (2006) with data from year 1965 to 2013. In Table 3.6, the estimated SOA are almost identical to previous research, the slight difference mainly come from the fact that the time intervals are different. The SOA from Fama and MacBeth (1973) two step procedure is 0.127 and 0.295 if demeaned. The estimated SOA of FE is 0.340, and 0.347 if year dummies are added, and if we sort the sample by MDR and only use the 50% observations in the middle, i.e. drop observations with MDR below first quartile and above third quartile, the estimated SOA is 0.369.

To see wether the SOA of the firms issued in hot IPO cycles are different from average firms, I report the sub sample estimation results in Table 3.7, which includes firms issued in hot IPO cycles only, with slightly different time span from year 1970 to 2010, to accommodate the SDC data availability. The SOA from Fama and MacBeth (1973) two step procedure is 0.172 and 0.184 if demeaned. The estimated SOA of FE is 0.381, and 0.387 if year dummies are added, and if we sort the sample by MDR and only use the 50% observations in the middle, i.e. drop observations with MDR below first quartile and above third quartile, the estimated SOA is 0.475. We can see that the estimated SOA are consistent with the full sample result, but significantly higher, except for demeaned FM two step procedure.

One possible explanation for the higher SOA for the firms issued in hot IPO cycle is that the these firms are better managed, and act more quickly in terms of capital structure adjustments, which in return, indicates they are truly higher quality firms. However, as discussed previously, these estimation methods are flawed, In the following sections I use system GMM estimation and DPF estimation to check the results.

Table 3.6: Preliminary estimation results for all firms

This table presents different estimation results for Eq. (3.12) using (1) Fama and MacBeth two step procedure, (2) fixed effect model, (3) Fama and MacBeth two step demeaned, (4) fixed effect model with year dummies, (5) instrumental variable approach, (6) instrumental variable approach with 50% MDR in the middle, (7) fixed effect with 50% MDR in the middle. The SOA estimations are consistent with previous research. See page 54 for more discussion. Consistent with previous research, there is no year dummies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FM	FM_demean	IV	IV_p50	FE	FE_year	FE_p50
MDR	0.873***	0.705***	0.708***	0.599***	0.660***	0.653***	0.631***
	(76.33)	(20.18)	(139.63)	(41.90)	(246.24)	(254.40)	(106.04)
EBIT_TA	-0.046***	-0.169**	-0.039***	-0.094***	-0.050***	-0.076***	-0.085***
	(-3.93)	(-2.23)	(-6.71)	(-10.63)	(-10.02)	(-15.47)	(-11.17)
MB	-0.000	0.002	-0.001	0.002	0.001**	-0.002***	0.004***
	(-0.21)	(0.31)	(-1.18)	(1.59)	(2.35)	(-3.80)	(3.79)
DEP_TA	-0.250***	-0.453*	-0.352***	-0.350***	-0.515***	-0.382***	-0.363***
	(-11.09)	(-2.00)	(-13.44)	(-9.08)	(-19.84)	(-15.33)	(-9.84)
LnTA	0.001	0.011**	0.018***	0.024***	0.014***	0.021***	0.024***
	(1.05)	(2.02)	(27.29)	(24.50)	(26.10)	(34.17)	(26.05)
FA_TA	0.026***	0.082***	0.062***	0.076***	0.090***	0.072***	0.077***
	(4.53)	(3.91)	(14.16)	(11.44)	(20.99)	(17.39)	(12.14)
RnD_DUM	-0.001	0.006	0.000	0.002	0.008***	0.001	0.001
	(-1.09)	(1.40)	(0.27)	(0.81)	(6.13)	(0.81)	(0.74)
RnD_TA	-0.132***	-0.112	-0.047*	-0.073*	-0.088***	-0.073***	-0.061*
	(-5.61)	(-0.82)	(-1.88)	(-1.90)	(-3.50)	(-3.04)	(-1.65)
Ind_Median	0.047***	0.004	0.008	0.017*	0.019***	0.027***	0.015
	(5.73)	(0.21)	(1.26)	(1.73)	(3.88)	(4.24)	(1.56)
IPO	0.000	0.002	-0.054***	-0.040***	-0.002***	-0.013***	-0.014***
	.	(0.20)	(-5.81)	(-3.12)	(-3.64)	(-10.04)	(-7.72)
N	121637	121637	114547	59954	121637	121637	63283
r2	0.776	0.655			0.468	0.524	0.379
speed	0.127	0.295	0.292	0.401	0.340	0.347	0.369
Half_Life	5.475	2.347	2.375	1.728	2.037	1.999	1.876

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Preliminary estimation results for firms issued in hot IPO cycles

This table presents different estimation results for Eq. (3.12) using (1) Fama and MacBeth two step procedure, (2) fixed effect model, (3) Fama and MacBeth two step demeaned, (4) fixed effect model with year dummies, (5) instrumental variable approach, (6) instrumental variable approach with 50% MDR in the middle, (7) fixed effect with 50% MDR in the middle. The dummy variable "Later" indicating a firm issued in the later part of a hot IPO cycle. See page 54 for more discussion. Consistent with previous research, there is no year dummies.

	(1) FM	(2) FM_demean	(3) IV	(4) IV_p50	(5) FE	(6) FE_year	(7) FE_p50
MDR	0.828***	0.816***	0.651***	0.458***	0.619***	0.613***	0.525***
	(31.52)	(5.92)	(38.50)	(8.76)	(83.19)	(84.40)	(28.47)
EBIT_TA	-0.169**	-0.062	-0.046***	-0.142***	-0.045***	-0.068***	-0.129***
	(-2.54)	(-1.07)	(-2.94)	(-5.60)	(-3.44)	(-5.33)	(-6.03)
MB	0.003	0.025	-0.001	-0.005	0.000	-0.002*	-0.001
	(0.99)	(0.49)	(-0.51)	(-1.21)	(0.20)	(-1.82)	(-0.51)
DEP_TA	-0.611***	-0.308*	-0.282***	-0.139	-0.462***	-0.330***	-0.188*
	(-3.02)	(-1.70)	(-4.03)	(-1.31)	(-6.73)	(-4.91)	(-1.83)
LnTA	0.002	-0.010	0.023***	0.034***	0.011***	0.024***	0.032***
	(1.45)	(-0.53)	(12.13)	(10.43)	(8.58)	(14.36)	(11.31)
FA_TA	0.061***	0.065*	0.080***	0.086***	0.102***	0.086***	0.089***
	(5.15)	(1.79)	(6.27)	(4.05)	(8.29)	(7.13)	(4.47)
RnD_DUM	-0.018	0.061	-0.001	0.002	0.003	0.001	0.002
	(-1.58)	(1.35)	(-0.14)	(0.30)	(0.76)	(0.28)	(0.36)
RnD_TA	0.073	-0.484	-0.021	-0.156	-0.054	-0.041	-0.101
	(0.40)	(-1.11)	(-0.37)	(-1.53)	(-0.95)	(-0.75)	(-1.03)
Ind_Median	0.111***	-0.066**	0.012	-0.036	0.007	0.014	-0.046
	(3.40)	(-2.67)	(0.59)	(-1.14)	(0.44)	(0.74)	(-1.57)
IPO	0.000	0.001	-0.029	0.004	0.000	-0.012	-0.030**
	.	(0.02)	(-1.30)	(0.12)	(0.13)	(-1.39)	(-2.40)
Later	0.001	0.000	.	.	.	.	.
	(0.17)	.	.	.	.	.	.
N	17103	17103	15937	7743	17103	17103	8263
r2	0.784	0.668			0.415	0.466	0.297
speed	0.172	0.184	0.349	0.542	0.381	0.387	0.475
Half_Life	4.036	3.769	1.984	1.278	1.821	1.791	1.460

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

System GMM estimator results on SOA

In Table 3.8, I report the System GMM estimator result of the SOA, with year 1965 to 2013 data. Estimating models control for both industry dummies and year dummies. The SOA form the system GMM estimator is -0.019, which is consistent with Iliev and Welch (2010), if the the industry dummies are added, it is 0.118.

In Table 3.9, I report the System GMM estimation result of the SOA with year 1965 to 2013 data, for the firms issue in IPO hot cycles. Estimating models control for both industry dummies and year dummies. The SOA form the system GMM estimator is -0.033, if the the industry dummies are added, it is 0.426. The SOA for firms issue in hot IPO cycles form both estimators are significantly higher than the average firms. This confirms the findings in the previous sections from FM, IV and FE estimators, that the firms issue in hot IPO cycles are more actively adjust their leverage ratios.

Autocorrelation test of second order is needed since first difference variables are involved, however, p-value of these tests are zeros, rejecting the hypothesis there is no autocorrelation. This can be fixed by ways such as setting the error terms follow MA(1) process, but I do not use this approach since this is not our main concern, and there is no need to fine tune the system GMM estimator. Sargan test of overidentifying restrictions shows the system GMM estimators may biased. Null hypothesis of this test is that the overidentifying restrictions are valid. The corresponding p-values are 0's for all sample system GMM estimations, are marginal (0.085) for system GMM estimation without industry dummies, and rejection (0.017) for system GMM estimation with industry dummies, which indicate the IV's may not be suitable, or may have weak IV problem. Besides, as discussed earlier, the system GMM estimator did not consider the fact that the variable being explained is limited between 0 and 1, which would bias the estimates. In the following section, I use DPF estimator to address the limited variable problem.

I put the preliminary estimation results and further estimation results including system GMM estimation results into Table 3.10. From this table, it is clear that firms

Table 3.8: Further regression results for all firms

This table presents different estimation results for Eq. (3.12) using (1) ordinary least square estimator, (2) fixed effect model, (3) instrumental variable approach, market debt ratio as leverage, (4) instrumental variable approach, book debt ratio as leverage, (5) PDP first-difference GMM model, (6) system GMM estimator, (7) system GMM estimator with industry dummies. See page 57 for more discussion. Year dummies are included.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	FE	IV_MDR	IV_BDR	FD_GMM	SYS_GMM	SYS_GMM_IND
MDR	0.869***	0.653***	0.633***	0.708***	0.722***	1.019***	0.882***
	(495.81)	(254.40)	(149.74)	(139.63)	(63.47)	(131.37)	(48.65)
EBIT_TA	-0.035***	-0.076***	-0.081***	-0.039***	0.255***	0.351***	0.325***
	(-8.33)	(-15.47)	(-14.40)	(-6.71)	(27.98)	(33.09)	(25.40)
MB	-0.002***	-0.002***	-0.004***	-0.001	0.020***	0.028***	0.026***
	(-4.47)	(-3.80)	(-6.37)	(-1.18)	(23.30)	(28.02)	(23.00)
DEP_TA	-0.260***	-0.382***	-0.375***	-0.352***	0.131***	0.324***	0.141**
	(-18.04)	(-15.33)	(-13.87)	(-13.44)	(2.63)	(5.13)	(2.24)
LnTA	0.000**	0.021***	0.022***	0.018***	0.004	-0.015***	-0.023***
	(2.54)	(34.17)	(31.65)	(27.29)	(1.57)	(-7.37)	(-5.82)
FA_TA	0.028***	0.072***	0.076***	0.062***	0.016	-0.073***	-0.014
	(15.15)	(17.39)	(16.96)	(14.16)	(1.54)	(-5.96)	(-1.02)
RnD_DUM	-0.002***	0.001	0.001	0.000	-0.001	-0.000	-0.000
	(-2.73)	(0.81)	(0.42)	(0.27)	(-0.38)	(-0.01)	(-0.17)
RnD_TA	-0.138***	-0.073***	-0.090***	-0.047*	0.397***	0.436***	0.423***
	(-12.23)	(-3.04)	(-3.48)	(-1.88)	(9.95)	(8.99)	(8.60)
Ind_Median	0.031***	0.027***	0.032***	0.008	-0.175***	-0.243***	-0.234***
	(9.45)	(4.24)	(4.68)	(1.26)	(-17.05)	(-18.67)	(-16.75)
IPO	-0.009***	-0.013***	-0.054***	-0.054***	0.030***	0.003	0.048***
	(-6.92)	(-10.04)	(-5.74)	(-5.81)	(13.86)	(1.41)	(15.45)
N	121637	121637	108659	114547	107220	121637	121190
r2	0.785	0.524					
ar1			-3.243	-11.056			
ar1p			0.001	0.000			
ar2					-6.780	-5.923	-6.191
ar2p					0.000	0.000	0.000
Sargan					2717.264	2474.833	1840.290
Sargan_p					0.000	0.000	0.000
speed	0.131	0.347	0.367	0.292	0.278	-0.019	0.118
Half_Life	2.298	0.868	0.820	1.031	1.083	-15.844	2.551

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = $\ln 2$/Speed (Years)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Further regression results for firms issue in hot IPO cycle

This table presents different estimation results for Eq. (3.12) using (1) ordinary least square estimator, (2) fixed effect model, (3) instrumental variable approach, market debt ratio as leverage, (4) instrumental variable approach, book debt ratio as leverage, (5) PDP first-difference GMM model, (6) system GMM estimator, (7) system GMM estimator with industry dummies. The dummy variable "Later" indicating a firm issued in the later part of a hot IPO cycle. See page 57 for more discussion. Year dummies are included.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	FE	IV_MDR	IV_BDR	FD_GMM	SYS_GMM	SYS_GMM_IND
MDR	0.866***	0.613***	0.598***	0.651***	0.584***	1.033***	0.574***
	(171.83)	(84.40)	(46.38)	(38.50)	(295.73)	(64.69)	(18.13)
EBIT_TA	-0.010	-0.068***	-0.068***	-0.046***	0.203***	0.327***	0.199***
	(-0.86)	(-5.33)	(-4.54)	(-2.94)	(64.40)	(16.10)	(9.87)
MB	-0.004***	-0.002*	-0.003*	-0.001	0.011***	0.020***	0.012***
	(-4.08)	(-1.82)	(-1.89)	(-0.51)	(33.62)	(12.59)	(7.85)
DEP_TA	-0.267***	-0.330***	-0.294***	-0.282***	0.220***	0.533***	0.310***
	(-7.41)	(-4.91)	(-4.01)	(-4.03)	(8.25)	(4.51)	(2.82)
LnTA	0.001*	0.024***	0.027***	0.023***	0.010***	-0.027***	0.014**
	(1.71)	(14.36)	(13.67)	(12.13)	(11.09)	(-9.54)	(2.17)
FA_TA	0.038***	0.086***	0.086***	0.080***	0.001	-0.065***	0.003
	(7.54)	(7.13)	(6.46)	(6.27)	(0.19)	(-2.78)	(0.11)
RnD_DUM	-0.002	0.001	-0.003	-0.001	-0.006***	-0.002	-0.003
	(-0.96)	(0.28)	(-0.67)	(-0.14)	(-4.33)	(-0.33)	(-0.47)
RnD_TA	-0.162***	-0.041	-0.026	-0.021	0.314***	0.239***	0.252***
	(-6.73)	(-0.75)	(-0.43)	(-0.37)	(19.82)	(3.39)	(4.07)
Ind_Median	0.041***	0.014	0.024	0.012	-0.113***	-0.227***	-0.136***
	(4.58)	(0.74)	(1.15)	(0.59)	(-30.26)	(-7.98)	(-4.70)
IPO	-0.017	-0.012	-0.035	-0.029	0.027***	-0.008*	0.044***
	(-1.45)	(-1.39)	(-1.49)	(-1.30)	(11.48)	(-1.90)	(5.17)
Later	0.002	.	.	.	0.000	-0.115***	-4.591*
	(1.31)	.	.	.	.	(-5.60)	(-1.71)
N	17103	17103	14740	15937	14484	17103	17028
r2	0.775	0.466					
ar1			-1.600	-4.702			
ar1p			0.110	0.000			
ar2					.	-0.474	-1.193
ar2p					.	0.635	0.233
sargan					.	538.778	432.123
sargan_p					.	0.000	0.000
speed	0.134	0.387	0.402	0.349	0.416	-0.033	0.426
Half_Life	5.173	1.791	1.724	1.984	1.666	-21.004	1.627

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: Summary of preliminary and further estimation results

This table summarizes preliminary (Table 3.6, Table 3.7) and further estimation results (Table 3.8, Table 3.9). From this table, it is obvious that firms issued in hot IPO cycles have greater SOA, except for FM demeaned estimator, since we know FM demeaned estimator is theoretically incorrect way to deal with fixed effect panel data, we can safely ignore it. See page 60 for more discussion.

Panel A: Preliminary results:							
	FM	FM_demean	IV	IV_p50	FE	FE_year	FE_p50
All firms	0.127	0.295	0.292	0.401	0.340	0.347	0.369
Firms issued in hot cycle	0.172	0.184	0.349	0.542	0.381	0.387	0.475
Panel B: Further results:							
	OLS	FE	IV_MDR	IV_BDR	FD_GMM	SYS_GMM	SYS_GMM_IND
All firms	0.131	0.347	0.367	0.292	0.278	-0.019	0.118
Firms issued in hot cycle	0.134	0.387	0.402	0.349	0.416	-0.033	0.426

issued in hot IPO cycles have greater SOA, except for FM demeaned estimator, since we know FM demeaned estimator is theoretically incorrect way to deal with fixed effect panel data, we can safely ignore it.

However, this is a technical weakness of the system GMM estimator applied on this data set. From Table 3.8 and Table 3.9 the Sargan test (also called Hansen test or J-test for overidentifying restrictions) shows the over-identifying restrictions are not valid, which means not all the instruments are exogenous. The output of the p-value of Sargan test presents strong evidence against the null hypothesis that the overidentifying restrictions are valid. Rejecting this null hypothesis implies the need to reconsider using system GMM model or the instruments, unless the rejection can be attributed to heteroskedasticity in the model. Sargan test is constructed such that under the null hypothesis if the over-identifying restrictions are valid, the statistic is asymptotically follows χ^2 distribution with $(m - k)$ degrees of freedom (where m is the number of instruments and k is the number of endogenous variables).

DPF estimation results on SOA

In the first tow columns of Table 3.11, I report the DPF estimation results for all firms between 1971 to 2012. The reason I use shorter time period is because DPF estimator by construction needs higher quality data. For all the samples the SOA from DPF estimator is 0.210, if industry dummies are included, it is 0.212. In the third and fourth columns of Table 3.11, I report the DPF estimation results for the firms issue in IPO hot cycle between 1971 to 2012. The SOA from DPF estimator is 0.235, if industry dummies are included, it is 0.235. In the fifth and sixth columns of Table 3.11, I report the DPF estimation results for the firms issue in IPO hot cycle between 1971 to 2012. The SOA from DPF estimator is 0.248, if industry dummies are included, it is 0.249.

These results confirm the previous finding that the firms issue in hot IPO cycles have higher SOA, even when the industry dummies are taken into considered. However, the firms issued in the later part of hot IPO cycles do not so significantly different in SOA with the firms issued in hot cycles.

In order to evaluate the properness of DPF estimator, which is in essence a Tobit estimator for panel data, we check the the ρ and sensitivity of quadrature approximation.

Firstly, the ρ in Table 3.11 is the percentage contribution of the panel-level variance component to the total variance

$$\rho = \frac{\sigma_\upsilon^2}{\sigma_\varepsilon^2 + \sigma_\upsilon^2} \tag{3.21}$$

for the regression model with panel-level random effects

$$y_{i,t} = \mathbf{x}'_{i,t}\boldsymbol{\beta} + \upsilon_i + \varepsilon_{i,t} \tag{3.22}$$

where $y_{i,t}$ is censored. If ρ is different from zero, we know that the panel estimator is different from the pooled estimator. In our case, the ρ ranges from 0.118 to 0.202,

Table 3.11: DPF estimation results

This table presents the DPF estimation results for: all firms with (1) and without (2) industry dummies; for firms issued in hot IPO cycles with (3) and without (4) industry dummies; for firms issued in later part of IPO cycles with (5) and without (6) industry dummies. See page 61 for more discussion.

	(1) DPF_ALL	(2) DPF_ALL_xi	(3) DPF_Raising	(4) DPF_Raising_xi	(5) DPF_Raising_Later	(6) DPF_Raising_xi_Later
MDR_L	0.790***	0.788***	0.765***	0.765***	0.752***	0.751***
	(235.79)	(235.36)	(87.62)	(86.75)	(66.39)	(64.69)
FNM_MDR	0.049***	0.048***	0.071***	0.068***	0.083***	0.082***
	(13.91)	(13.48)	(6.22)	(5.70)	(5.26)	(4.99)
EBIT_TA_L	0.018***	0.017***	0.021	0.020	0.036*	0.034*
	(3.11)	(2.91)	(1.42)	(1.36)	(1.87)	(1.80)
MB_L	0.006***	0.006***	0.003**	0.003**	0.003*	0.003*
	(9.71)	(9.66)	(2.29)	(2.36)	(1.67)	(1.73)
DEP_TA_L	-0.467***	-0.465***	-0.423***	-0.427***	-0.344***	-0.351***
	(-15.86)	(-15.76)	(-5.57)	(-5.61)	(-3.44)	(-3.50)
LnTA_L	0.011***	0.011***	0.007***	0.007***	0.008***	0.008***
	(17.09)	(17.25)	(4.72)	(4.87)	(4.00)	(4.16)
FA_TA_L	0.089***	0.090***	0.099***	0.100***	0.087***	0.089***
	(18.10)	(18.26)	(7.21)	(7.31)	(4.86)	(4.97)
RnD_DUM_L	0.005***	0.005***	0.010**	0.009*	0.008	0.007
	(3.20)	(3.05)	(2.23)	(1.93)	(1.33)	(1.18)
RnD_TA_L	-0.018	-0.014	0.005	0.007	-0.064	-0.062
	(-0.60)	(-0.47)	(0.07)	(0.11)	(-0.79)	(-0.75)
Ind_Median_L	-0.078***	-0.076***	-0.074***	-0.070***	-0.061***	-0.057**
	(-13.15)	(-12.78)	(-4.25)	(-4.00)	(-2.69)	(-2.49)
IPO_L	-0.003***	-0.003***	0.001	0.001	-0.000	-0.000
	(-5.83)	(-5.82)	(0.61)	(0.64)	(-0.11)	(-0.06)
MEAN_EBIT_TA	-0.251***	-0.262***	-0.174***	-0.182***	-0.211***	-0.233***
	(-19.38)	(-20.04)	(-5.03)	(-5.19)	(-4.40)	(-4.75)
MEAN_MB	-0.017***	-0.017***	-0.021***	-0.021***	-0.025***	-0.024***
	(-15.49)	(-14.61)	(-7.83)	(-7.67)	(-6.76)	(-6.29)
MEAN_DEP_TA	0.239***	0.252***	0.189*	0.259**	0.163	0.293**
	(5.66)	(5.87)	(1.76)	(2.35)	(1.14)	(1.98)
MEAN_LnTA	-0.009***	-0.009***	-0.007***	-0.006***	-0.008***	-0.007***
	(-13.26)	(-12.47)	(-3.92)	(-3.40)	(-3.17)	(-2.88)
MEAN_FA_TA	-0.057***	-0.036***	-0.044***	-0.028	-0.034	-0.019
	(-9.21)	(-5.54)	(-2.58)	(-1.52)	(-1.52)	(-0.76)
MEAN_RnD_DUM	-0.005**	-0.010***	-0.012**	-0.020***	-0.011	-0.019**
	(-2.17)	(-4.09)	(-1.98)	(-3.05)	(-1.33)	(-2.11)
MEAN_RnD_TA	-0.243***	-0.291***	-0.279***	-0.276***	-0.163	-0.161
	(-6.61)	(-7.60)	(-3.53)	(-3.32)	(-1.57)	(-1.46)
MEAN_Ind_Median	0.175***	0.212***	0.198***	0.305***	0.186***	0.318***
	(20.12)	(13.80)	(8.15)	(6.87)	(5.70)	(5.33)
MEAN_IPO	0.001	0.003**	-0.006**	0.000	-0.006	0.001
	(0.49)	(2.04)	(-2.02)	(0.11)	(-1.51)	(0.27)
N	111984	111573	16967	16892	9654	9594
N_group	11698	11650	2192	2184	1253	1248
pseudo_R2	0.764	0.764	0.753	0.754	0.759	0.760
sigma_u	0.042	0.041	0.051	0.050	0.056	0.055
sigma_e	0.114	0.114	0.113	0.114	0.112	0.112
rho	0.121	0.118	0.170	0.160	0.202	0.192
speed	0.210	0.212	0.235	0.235	0.248	0.249
Half_Life	3.301	3.270	2.951	2.946	2.800	2.779

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

which is different from zero, indicating the panel estimator is more appropriate than the pooled estimator.

Secondly, I check the sensitivity of quadrature approximation. Random-effects panel data Tobit regression use Gauss-Hermite quadrature to compute the log likelihood. The goodness of the random-effects model depends on good quadrature approximation. To check if we have a good quadrature approximation, we can run the model with different integration points, 8 and 16, the compare the change in coefficients. If the change is by less than 0.01%, then the quadrature is reliably approximating the likelihood, if the difference is greater than 1%, then it is not. Most the differences of coefficients are less than 0.01%. (Detailed results are omitted to save space but can be requested from corresponding author.)

Lastly, I also wish to measure how well Tobit model fits. This is useful when comparing competing models. One method of doing this is to compare the predicted values based on the Tobit model, $\widehat{MDR}_{i,t}$, to the observed values, $MDR_{i,t}$ in the dataset. First we compute the predicted values of $MDR_{i,t}$ based on the Tobit model. Next we correlate the observed values of MDR with the predicted values $\widehat{MDR}_{i,t}$. The pseudo R-squared is simply $R \times R$. The estimated pseudo R-squared is around 0.75.

3.5 Robustness

In this section, I show that the difference in SOA is robust over different estimation horizons, over firms with different sizes, over different time periods, over alternative leverage measures, over alternative classification method, and to ease of accessing capital markets.

3.5.1 Stability over estimation horizons

I start the robustness check from alternative estimation horizon specifications. Specifically, I extend the time horizon from 1 year to 2, 3 and 4 years to see if the tendency

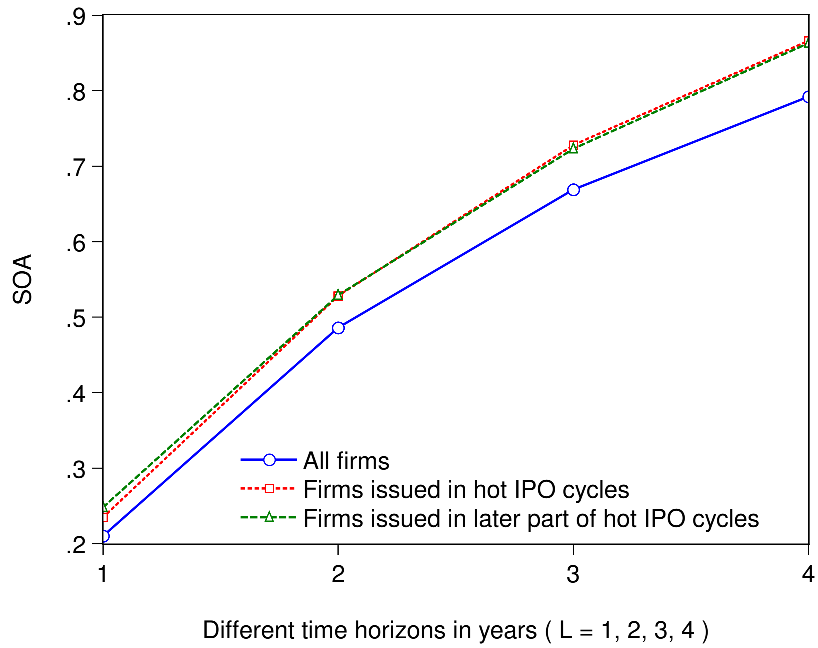


Figure 3.6: Stability over different forecast horizons

This figure shows that the firms issued in hot IPO cycles have higher SOA than average firms, at all four estimation horizons. The estimation horizons is from 1 year to 4 years. See page 63 for more discussions.

that firms issued in hot IPO cycle have higher SOA would still remains. In Table 3.12 I report the results of DPF estimation over time horizon 1, 2, 3 and 4 years for all firms, firms issued in hot IPO cycles, and firms issued in later part of IPO cycles. In Fig. 3.6, I summarize the major results of Table 3.12, and we can see that the SOA of the firms issued in hot IPO cycles are higher at all estimation horizons. Therefore, my finding is robust over estimation horizons.

Table 3.12: Stability over different forecast horizons

This is table presents the DPF estimation results over different forecast horizons. (1)-(4) shows DPF estimation results for all firms over 1 year to 4 years forecast horizons. (5)-(8) shows DPF estimation results for firms issued in hot IPO cycles over 1 year to 4 years forecast horizons. (9)-(12) shows DPF estimation results for firms issued in later part of hot IPO cycles over 1 year to 4 years forecast horizons. See page 63 for more discussion.

	(1) DPF_ALL_k1	(2) DPF_ALL_k2	(3) DPF_ALL_k3	(4) DPF_ALL_k4	(5) DPF_hot_k1	(6) DPF_hot_k2	(7) DPF_Raising_k3	(8) DPF_Raising_k4	(9) DPF_Raising_Later_k1	(10) DPF_hot_Later_k2	(11) DPF_hot_Later_k3	(12) DPF_hot_Later_k4
MDR_L	0.790***	0.514***	0.331***	0.208***	0.765***	0.472***	0.272***	0.134***	0.752***	0.471***	0.277***	0.137***
	(235.79)	(127.03)	(73.71)	(43.82)	(87.62)	(42.33)	(23.03)	(10.54)	(66.39)	(32.33)	(18.16)	(8.17)
FNM_MDR	0.049***	0.122***	0.173***	0.215***	0.071***	0.145***	0.179***	0.201***	0.083***	0.127***	0.227***	0.260***
	(13.91)	(19.55)	(21.27)	(20.36)	(6.22)	(7.22)	(10.53)	(10.62)	(5.26)	(5.66)	(10.56)	(9.13)
EBIT_TA_L	0.018***	0.007	0.025***	0.035***	0.021	-0.012	-0.017	-0.004	0.036*	0.011	0.007	0.021
	(3.11)	(0.91)	(3.02)	(4.03)	(1.42)	(-0.62)	(-0.79)	(-0.17)	(1.87)	(0.46)	(0.25)	(0.70)
MB_L	0.006***	0.007***	0.003***	0.000	0.003**	0.004**	0.002	0.000	0.003*	0.005**	0.001	-0.001
	(9.71)	(9.11)	(3.97)	(0.51)	(2.29)	(2.48)	(1.21)	(0.22)	(1.67)	(2.06)	(0.52)	(-0.31)
DEP_TA_L	-0.467***	-0.689***	-0.745***	-0.671***	-0.423***	-0.690***	-0.814***	-0.742***	-0.344***	-0.552***	-0.754***	-0.709***
	(-15.86)	(-17.91)	(-17.30)	(-14.64)	(-5.57)	(-6.94)	(-7.32)	(-6.11)	(-3.44)	(-4.27)	(-5.23)	(-4.49)
LnTA_L	0.011***	0.009***	0.005***	0.005***	0.007***	0.006***	0.006***	0.004**	0.008***	0.007***	0.007***	0.004
	(17.09)	(11.13)	(5.86)	(4.92)	(4.72)	(3.43)	(2.98)	(1.98)	(4.00)	(2.89)	(2.59)	(1.47)
FA_TA_L	0.089***	0.116***	0.113***	0.095***	0.099***	0.149***	0.141***	0.139***	0.087***	0.137***	0.138***	0.129***
	(18.10)	(18.18)	(15.83)	(12.63)	(7.21)	(8.33)	(7.08)	(6.49)	(4.86)	(5.86)	(5.32)	(4.63)
RnD_DUM_L	0.005***	0.001	-0.001	0.003	0.010**	0.008	0.002	0.008	0.008	0.003	-0.001	0.000
	(3.20)	(0.63)	(-0.61)	(1.31)	(2.23)	(1.23)	(0.27)	(1.00)	(1.33)	(0.37)	(-0.09)	(0.03)
RnD_TA_L	-0.018	-0.072*	-0.098**	-0.103**	0.005	0.040	0.076	0.081	-0.064	-0.055	-0.070	-0.025
	(-0.60)	(-1.87)	(-2.27)	(-2.25)	(0.07)	(0.48)	(0.80)	(0.78)	(-0.79)	(-0.53)	(-0.60)	(-0.19)
Ind_Median_L	-0.078***	-0.170***	-0.126***	-0.089***	-0.074***	-0.128***	-0.088***	-0.102***	-0.061***	-0.123***	-0.076**	-0.096***
	(-13.15)	(-22.71)	(-15.29)	(-10.29)	(-4.25)	(-5.75)	(-3.57)	(-3.84)	(-2.69)	(-4.29)	(-2.42)	(-2.81)
IPO_L	-0.003***	-0.005***	0.004***	0.003***	0.001	0.003*	0.011***	0.008***	-0.000	0.000	0.008***	0.005*
	(-5.83)	(-7.45)	(5.02)	(3.59)	(0.61)	(1.90)	(5.87)	(3.74)	(-0.11)	(0.18)	(3.16)	(1.86)
MEAN_EBIT_TA	-0.251***	-0.479***	-0.659***	-0.794***	-0.174***	-0.379***	-0.459***	-0.450***	-0.211***	-0.470***	-0.590***	-0.704***
	(-19.38)	(-19.98)	(-19.57)	(-15.69)	(-5.03)	(-6.35)	(-6.17)	(-5.78)	(-4.40)	(-5.62)	(-6.32)	(-7.26)
MEAN_MB	-0.017***	-0.030***	-0.033***	-0.035***	-0.021***	-0.035***	-0.037***	-0.049***	-0.025***	-0.041***	-0.035***	-0.040***
	(-15.49)	(-14.36)	(-10.76)	(-8.03)	(-7.83)	(-6.69)	(-7.03)	(-8.59)	(-6.76)	(-6.36)	(-5.16)	(-5.08)
MEAN_DEP_TA	0.239***	0.133*	0.048	-0.082	0.189*	0.112	-0.041	-0.246	0.163	0.077	0.066	-0.195
	(5.66)	(1.92)	(0.54)	(-0.87)	(1.76)	(0.64)	(-0.21)	(-1.24)	(1.14)	(0.40)	(0.30)	(-0.76)
MEAN_LnTA	-0.009***	-0.006***	-0.000	0.003**	-0.007***	-0.005	-0.006**	-0.002	-0.008***	-0.005	-0.008**	-0.004
	(-13.26)	(-5.53)	(-0.16)	(2.08)	(-3.92)	(-1.60)	(-2.05)	(-0.74)	(-3.17)	(-1.50)	(-2.08)	(-0.99)
MEAN_FA_TA	-0.057***	-0.045***	-0.022**	0.016	-0.044***	-0.045*	-0.006	0.012	-0.034	-0.061*	-0.011	0.019
	(-9.21)	(-4.80)	(-1.98)	(1.33)	(-2.58)	(-1.77)	(-0.23)	(0.42)	(-1.52)	(-1.95)	(-0.32)	(0.50)
MEAN_RnD_DUM	-0.005**	-0.002	0.006	0.003	-0.012**	-0.017	-0.042***	-0.066***	-0.011	-0.010	-0.039***	-0.059***
	(-2.17)	(-0.51)	(1.43)	(0.70)	(-1.98)	(-1.41)	(-3.95)	(-5.67)	(-1.33)	(-0.80)	(-2.93)	(-3.87)
MEAN_RnD_TA	-0.243***	-0.366***	-0.380***	-0.341***	-0.279***	-0.523***	-0.616***	-0.617***	-0.163	-0.434***	0.090	0.213
	(-6.61)	(-6.29)	(-5.48)	(-4.55)	(-3.53)	(-4.36)	(-4.63)	(-4.15)	(-1.57)	(-3.00)	(0.54)	(1.09)
MEAN_Ind_Median	0.175***	0.372***	0.393***	0.369***	0.198***	0.363***	0.366***	0.443***	0.186***	0.403***	0.317***	0.395***
	(20.12)	(26.31)	(22.54)	(17.93)	(8.15)	(9.23)	(9.01)	(9.72)	(5.70)	(7.92)	(6.55)	(7.32)
MEAN_IPO	0.001	-0.004*	-0.018***	-0.019***	-0.006**	-0.013**	-0.023***	-0.015**	-0.006	-0.013**	-0.022***	-0.017**
	(0.49)	(-1.74)	(-7.14)	(-6.04)	(-2.02)	(-2.53)	(-3.70)	(-2.01)	(-1.51)	(-2.02)	(-2.70)	(-1.99)
N	111984	99905	89890	81183	16967	14645	12814	11289	9654	8346	7303	6448
N_group	11698	10282	9209	8304	2192	1886	1625	1413	1253	1079	923	812
pseudo_R2	0.764	0.590	0.481	0.410	0.753	0.575	0.464	0.387	0.759	0.589	0.489	0.405
sigma_u	0.042	0.091	0.114	0.124	0.051	0.104	0.131	0.147	0.056	0.108	0.132	0.151
sigma_e	0.114	0.137	0.143	0.143	0.113	0.134	0.140	0.141	0.112	0.131	0.136	0.137
rho	0.121	0.308	0.385	0.431	0.170	0.372	0.466	0.521	0.202	0.401	0.486	0.546
speed	0.210	0.486	0.669	0.792	0.235	0.528	0.728	0.866	0.248	0.529	0.723	0.863
Half_Life	3.301	1.427	1.037	0.875	2.951	1.312	0.953	0.801	2.800	1.309	0.958	0.803

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.5.2 Stability across firm sizes

Firm size is another factor that may compromise the robustness of my finding. Thus, I test the stability of the finding across firm sizes. In Table 3.13, I report the DPF estimation results by different firm sizes. The firm size is measured by market equity value, and sorted into 4 groups by firm size. The first group are firms with smallest market equity values, the fourth group are firms with largest market equity values in that year. The firm size is measure by market equity value (Compustat variable: EMV = MV-TD).

I summarize major findings of Table 3.13 into Fig. 3.7. We can see that the SOA for firms issued in hot IPO cycles are consistently higher. This indicates that the finding that firms issued in hot IPO cycles are more active on average in leverage adjustment is robust across firm sizes.

3.5.3 Stability over time

Stock market crashes and bear markets may have impacts on the robustness of our finding. There are two competing theories about the relation between SOA and market downturns. One theory is that firms do not do anything unless there is a crisis, which implies crash is positively related to SOA. The other theory is that recession make leverage change difficult, which implies crash is negatively related to SOA. No matter which theory dominates, generally people agree crashes will affect SOA. In this section I test wether my finding is robust enough to survive the influence of stock market crashes and bear markets.

In order to test the stability over time, I divide the time interval into six segments: (1) year 1970 to year 1986, (2) year 1987 to year 1991 (Black Monday Oct 19 1987, Friday the 13th mini-crash Oct 13 1989, 1990-1991 Recession July 1990), (3) year 1992 to year 1996, (4) year 1997 to year 2002 (Oct 27 1997 mini-crash, Dot-com bubble March 10 2000, September 11 attacks Sep 11 2001, Stock market downturn

Table 3.13: Stability across firm sizes

This table reports the DPF estimation results by different firm sizes, which is measured by market equity value. Firms are sorted into 4 groups by firm size, first group is the smallest, fourth group is the largest. (1)-(4) report DPF estimation results for all firms, (1) is smallest, (4) is largest. (5)-(8) report results for firms issued in hot IPO cycles. (9)-(12) report results for firms issued in later part of hot IPO cycles. See 66 for more discussion.

	(1) DPF_A_g1	(2) DPF_A_g2	(3) DPF_A_g3	(4) DPF_A_g4	(5) DPF_R_g1	(6) DPF_R_g2	(7) DPF_R_g3	(8) DPF_R_g4	(9) DPF_L_g1	(10) DPF_L_g2	(11) DPF_L_g3	(12) DPF_L_g4
MDR_L	0.728***	0.724***	0.782***	0.821***	0.707***	0.695***	0.772***	0.783***	0.690***	0.699***	0.760***	0.756***
	(87.12)	(96.34)	(122.88)	(166.41)	(29.67)	(34.75)	(46.82)	(58.64)	(22.70)	(24.91)	(35.39)	(42.20)
FNM_MDR	0.038***	-0.001	0.004	0.006	0.013	0.002	-0.033	0.030**	0.029	0.026	-0.032	0.046**
	(5.52)	(-0.06)	(0.63)	(1.43)	(0.71)	(0.08)	(-1.59)	(2.07)	(1.17)	(0.63)	(-1.16)	(2.22)
EBIT_TA_L	-0.008	-0.031**	0.016	0.030***	-0.011	-0.034	0.005	0.044**	-0.009	0.023	0.015	0.036
	(-0.52)	(-2.49)	(1.44)	(3.73)	(-0.22)	(-1.06)	(0.20)	(2.21)	(-0.15)	(0.55)	(0.42)	(1.40)
MB_L	0.051***	0.015***	0.002	0.002***	0.066***	0.020***	-0.001	-0.000	0.068***	0.022***	-0.000	-0.001
	(15.17)	(8.85)	(1.49)	(2.97)	(6.12)	(4.85)	(-0.30)	(-0.33)	(4.48)	(3.99)	(-0.04)	(-0.50)
DEP_TA_L	-0.479***	-0.165**	-0.568***	-0.375***	-0.628**	-0.122	-0.381***	-0.322***	-0.565*	0.165	-0.188	-0.355***
	(-5.79)	(-2.32)	(-9.79)	(-9.69)	(-2.34)	(-0.66)	(-2.72)	(-3.31)	(-1.84)	(0.70)	(-0.97)	(-2.70)
LnTA_L	0.046***	0.041***	0.013***	0.001**	0.042***	0.053***	0.013***	-0.002	0.043***	0.064***	0.007*	0.000
	(19.92)	(18.39)	(9.55)	(2.27)	(6.56)	(8.70)	(4.13)	(-1.01)	(5.13)	(7.65)	(1.81)	(0.13)
FA_TA_L	0.070***	0.129***	0.115***	0.045***	0.020	0.094***	0.153***	0.065***	0.012	0.031	0.171***	0.056**
	(5.60)	(10.23)	(11.39)	(7.08)	(0.52)	(2.82)	(5.86)	(3.56)	(0.26)	(0.73)	(4.91)	(2.29)
RnD_DUM_L	0.012***	0.006	0.002	0.003	0.018	0.014	0.004	0.009	0.016	0.024*	-0.006	0.008
	(3.01)	(1.54)	(0.66)	(1.32)	(1.27)	(1.34)	(0.46)	(1.50)	(0.96)	(1.69)	(-0.55)	(1.00)
RnD_TA_L	-0.144	0.058	0.004	-0.039	0.387	0.064	-0.030	-0.052	0.154	-0.046	-0.043	-0.030
	(-1.38)	(0.87)	(0.07)	(-1.07)	(1.04)	(0.43)	(-0.26)	(-0.68)	(0.32)	(-0.25)	(-0.28)	(-0.32)
Ind_Median_L	-0.064***	-0.067***	-0.059***	-0.062***	-0.113**	-0.020	-0.031	-0.069***	-0.127**	-0.017	-0.003	-0.050
	(-4.48)	(-4.48)	(-4.72)	(-7.87)	(-2.42)	(-0.48)	(-0.92)	(-2.86)	(-2.20)	(-0.31)	(-0.07)	(-1.64)
IPO_L	-0.005***	-0.006***	-0.002**	-0.000	0.002	-0.004	0.001	0.002	0.005	-0.010**	-0.002	0.002
	(-3.04)	(-4.09)	(-2.09)	(-0.06)	(0.38)	(-1.25)	(0.20)	(1.35)	(0.80)	(-2.02)	(-0.53)	(1.07)
MEAN_EBIT_TA	-0.188***	-0.126***	-0.204***	-0.143***	-0.295***	-0.111*	-0.113**	-0.124***	-0.254*	-0.191**	-0.092	-0.170***
	(-5.53)	(-4.71)	(-8.73)	(-8.92)	(-2.64)	(-1.70)	(-1.99)	(-2.95)	(-1.83)	(-2.21)	(-1.18)	(-2.82)
MEAN_MB	-0.024***	0.003	0.006***	-0.013***	-0.020	0.005	0.004	-0.011***	-0.019	0.012	0.001	-0.012***
	(-4.19)	(1.07)	(2.76)	(-10.59)	(-0.96)	(0.63)	(0.83)	(-3.85)	(-0.75)	(1.07)	(0.20)	(-3.01)
MEAN_DEP_TA	0.303***	0.065	0.461***	0.333***	0.489	0.061	0.307*	0.236*	0.589	-0.330	0.162	0.281
	(2.86)	(0.65)	(5.86)	(6.59)	(1.56)	(0.24)	(1.71)	(1.80)	(1.63)	(-0.96)	(0.66)	(1.53)
MEAN_LnTA	-0.032***	-0.006**	0.010***	0.004***	-0.031***	-0.013*	0.020***	0.011***	-0.030***	-0.018*	0.028***	0.012***
	(-13.57)	(-2.09)	(5.59)	(4.84)	(-4.62)	(-1.75)	(4.21)	(5.10)	(-3.45)	(-1.80)	(4.40)	(3.87)
MEAN_FA_TA	-0.070***	-0.098***	-0.076***	-0.024***	-0.010	-0.049	-0.097***	-0.039*	-0.036	0.015	-0.096**	-0.024
	(-4.72)	(-6.25)	(-6.31)	(-3.25)	(-0.23)	(-1.18)	(-3.20)	(-1.79)	(-0.66)	(0.27)	(-2.38)	(-0.80)
MEAN_RnD_DUM	-0.011**	-0.002	0.006	-0.004	-0.011	-0.005	-0.012	-0.021***	-0.007	-0.006	0.002	-0.026**
	(-2.03)	(-0.44)	(1.31)	(-1.46)	(-0.66)	(-0.37)	(-1.03)	(-2.68)	(-0.34)	(-0.30)	(0.12)	(-2.46)
MEAN_RnD_TA	-0.402***	-0.321***	-0.289***	-0.074*	-0.885**	-0.539***	-0.242*	-0.011	-0.792	-0.400*	-0.210	0.037
	(-3.04)	(-3.90)	(-4.23)	(-1.77)	(-2.15)	(-2.95)	(-1.81)	(-0.13)	(-1.51)	(-1.73)	(-1.17)	(0.30)
MEAN_Ind_Median	0.113***	0.108***	0.103***	0.088***	0.144**	0.138**	0.090**	0.108***	0.168**	0.128*	0.050	0.074*
	(5.61)	(5.15)	(6.05)	(8.46)	(2.37)	(2.56)	(2.06)	(3.41)	(2.27)	(1.73)	(0.84)	(1.68)
MEAN_IPO	0.011***	0.021***	0.011***	0.000	0.007	0.015**	0.000	-0.001	0.009	0.017**	0.004	0.002
	(3.87)	(7.97)	(5.20)	(0.23)	(0.97)	(2.40)	(0.04)	(-0.11)	(0.94)	(2.06)	(0.60)	(0.28)
N	21693	23145	26769	40377	2433	3655	4480	6399	1542	1925	2599	3588
N_group	2895	2900	2892	3011	357	574	622	639	234	314	353	352
pseudo_R2	0.692	0.653	0.695	0.742	0.635	0.644	0.715	0.720	0.635	0.644	0.719	0.736
sigma_u	0.040	0.043	0.030	0.016	0.032	0.048	0.030	0.027	0.034	0.049	0.033	0.032
sigma_e	0.131	0.128	0.113	0.089	0.135	0.125	0.114	0.089	0.133	0.122	0.114	0.087
rho	0.084	0.102	0.064	0.030	0.054	0.128	0.063	0.081	0.062	0.140	0.076	0.122
speed	0.272	0.276	0.218	0.179	0.293	0.305	0.228	0.217	0.310	0.301	0.240	0.244
Half_Life	2.544	2.509	3.183	3.864	2.365	2.274	3.037	3.194	2.238	2.306	2.884	2.842

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

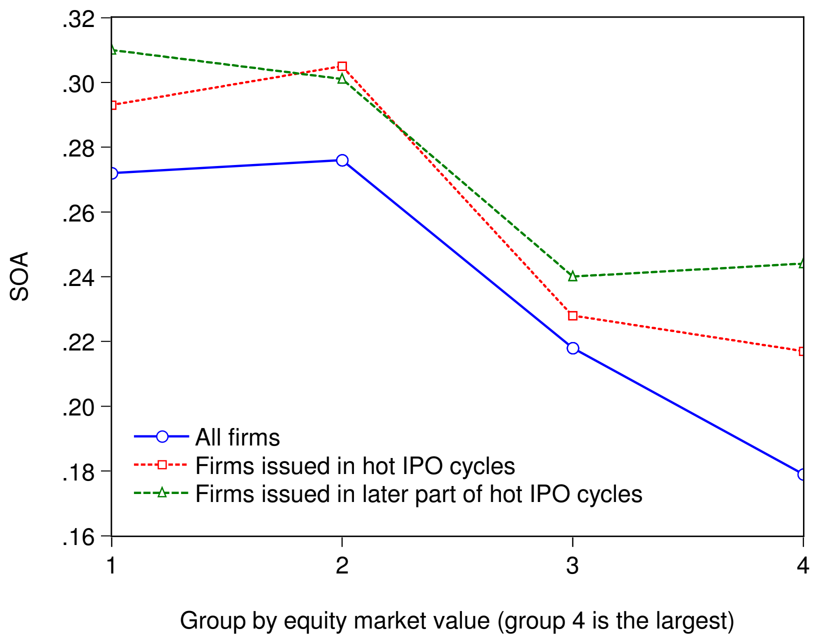


Figure 3.7: Stability across firm sizes

This figure shows that the firms issued in hot IPO cycle have higher SOA than average firms, at all four firm size groups. The firm size is measure by market equity value (Compustat variable: EMV = MV-TD). See page 66 for more discussions.

of 2002), (5) year 2003 to year 2006, (6) year 2007 to year 2012 (United States bear market of 2007-2009, Late-2000s financial crisis, 2010 Flash Crash, August 2011 stock markets fall).

In Table 3.14, I report the DPF estimation results for three group (all firms, firms issued in hot IPO cycles, firms issued in later part of hot IPO cycles) of firms over the above mentioned time intervals. We can see that SOA for firms issued in hot cycles are faster before 2003, but slower afterwards. Fig. 3.8 summarizes the major findings in Table 3.14. This figure shows the difference in terms of SOA for average frims and firms issued in hot IPO cycles is stable over time. However, the relation that firms issued in hot cycle always have a higher SOA is not stable. There is a structual change around year 2003, after that, the SOA for average firms are higher than those for firms issued in hot IPO cycles and firms issued in later part of hot cycles.

3.5.4 Stability over alternative “leverage” definition: BDR

In this section, I test whether difference in SOA is robust to alternative definition of debt leverage. Specifically, I use book debt ratio (BDR) instead of market debt ratio (MDR). In Table 3.15 I report the results of DPF estimators with BDR being the explained variable, and run the regression on all samples, firms issued in hot IPO cycles and firms issued in later part of hot IPO cycles. I find that the SOA of the firms issued in the later part of hot IPO cycle to be 0.226 which is faster than average firms’ SOA 0.182, and the firms issued in hot IPO cycles 0.213. Therefore, the finding that firms issued in hot IPO cycle have different SOA is robust to alternative leverage definition.

Next, using the BDR as leverage measure, I do robustness check over different forecast horizons, across firms sizes, and over time, similar to those in previous sections. The estimation results are omitted to save space, and the results are summarized in Fig. 3.9, in which we can see that under alternative leverage measure, the previous findings still hold. In specific, Fig. 3.9a shows that under different estimation horizon,

Table 3.14: Stability over time

This table reports the DPF estimation results over six time periods sizes, (1)-(6) report DPF estimation results for all firms from period 1 to period 6. (7)-(12) report results for firms issued in hot IPO cycles from period 1 to period 6. (13)-(18) report results for firms issued in later part of hot IPO cycles from period 1 to period 6. See page 66 for more discussion.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	DPF_A_t1	DPF_A_t2	DPF_A_t3	DPF_A_t4	DPF_A_t5	DPF_A_t6	DPF_R_t1	DPF_R_t2	DPF_R_t3	DPF_R_t4	DPF_R_t5	DPF_R_t6	DPF_L_t1	DPF_L_t2	DPF_L_t3	DPF_L_t4	DPF_L_t5	DPF_L_t6
MDR_L	0.774***	0.868***	0.834***	0.809***	0.763***	0.812***	0.711***	0.847***	0.795***	0.787***	0.799***	0.902***	0.722***	0.738***	0.795***	0.725***	0.859***	0.864***
	(109.39)	(76.52)	(104.80)	(78.72)	(82.00)	(53.72)	(27.66)	(29.90)	(37.25)	(37.76)	(33.24)	(30.28)	(21.07)	(15.94)	(29.93)	(23.56)	(31.19)	(23.47)
FNM_MDR	0.064***	0.030***	0.005	0.030***	0.022***	0.031***	0.055***	0.048**	0.027	0.092***	0.062***	0.017	0.063**	0.098**	0.031	0.125***	0.008	0.022
	(11.47)	(3.96)	(0.90)	(4.03)	(3.20)	(3.45)	(2.65)	(2.00)	(1.46)	(4.31)	(2.65)	(0.75)	(2.25)	(2.35)	(1.27)	(3.87)	(0.29)	(0.77)
EBIT_TA_L	-0.003	0.035**	0.051***	0.065***	-0.031*	0.045***	-0.038	0.011	0.108***	0.063*	0.077*	0.115***	0.013	-0.014	0.120**	0.069	0.119**	0.081
	(-0.32)	(2.07)	(3.44)	(4.30)	(-1.84)	(2.67)	(-1.12)	(0.28)	(3.18)	(1.96)	(1.87)	(2.81)	(0.30)	(-0.26)	(2.57)	(1.64)	(2.29)	(1.57)
MB_L	0.008***	0.016***	0.007***	0.011***	0.014***	0.006***	0.008**	0.017***	-0.001	0.007**	0.005	0.003	0.005	0.017**	0.004	0.006	0.000	0.005
	(6.74)	(7.28)	(4.39)	(7.62)	(7.46)	(3.23)	(2.17)	(3.56)	(-0.30)	(2.30)	(1.21)	(0.58)	(1.18)	(2.52)	(0.86)	(1.58)	(0.06)	(0.86)
DEP_TA_L	-0.784***	-0.415***	-0.270***	-0.291***	-0.118	-0.170*	-0.677***	-0.386*	-0.527***	-0.416**	-0.206	0.002	-0.292	-0.259	-0.592**	-0.194	-0.502*	0.014
	(-13.84)	(-4.94)	(-3.70)	(-3.65)	(-1.39)	(-1.69)	(-3.37)	(-1.93)	(-2.85)	(-2.34)	(-0.95)	(0.01)	(-1.16)	(-0.95)	(-2.45)	(-0.82)	(-1.89)	(0.04)
LnTA_L	0.014***	0.010***	0.018***	0.020***	0.012***	0.015***	0.013***	0.008	0.024***	0.021***	0.019***	0.009*	0.017***	0.020**	0.024***	0.021***	0.014**	0.008
	(9.59)	(4.47)	(9.90)	(9.81)	(5.82)	(6.51)	(2.72)	(1.54)	(5.73)	(4.68)	(3.42)	(1.65)	(2.84)	(2.52)	(4.60)	(3.40)	(2.21)	(1.13)
FA_TA_L	0.067***	0.065***	0.071***	0.075***	0.034**	0.085***	0.040	0.052	0.054	0.112***	0.124***	0.089**	-0.063	0.143**	0.071	0.074*	0.143***	0.069
	(7.30)	(4.43)	(5.50)	(5.21)	(2.21)	(5.09)	(1.27)	(1.31)	(1.52)	(3.31)	(2.99)	(2.21)	(-1.52)	(2.56)	(1.51)	(1.69)	(3.06)	(1.29)
RnD_DUM_L	0.008***	0.011**	0.002	-0.003	-0.010	0.006	0.022**	-0.015	0.006	0.012	0.002	-0.004	0.007	-0.022	0.021	0.010	-0.007	-0.000
	(3.51)	(2.01)	(0.43)	(-0.52)	(-1.64)	(0.93)	(2.33)	(-1.00)	(0.61)	(0.94)	(0.11)	(-0.33)	(0.59)	(-0.99)	(1.60)	(0.57)	(-0.34)	(-0.00)
RnD_TA_L	0.011	0.101	0.174**	-0.071	0.111	0.002	0.120	-0.044	0.175	0.145	0.279	0.138	-0.059	-0.138	0.192	0.035	0.473*	0.403
	(0.20)	(1.17)	(2.46)	(-0.90)	(1.17)	(0.02)	(0.77)	(-0.25)	(1.22)	(0.92)	(1.41)	(0.73)	(-0.30)	(-0.57)	(0.99)	(0.17)	(1.90)	(1.64)
Ind_Median_L	-0.191***	-0.085***	-0.170***	-0.108***	-0.042*	-0.156***	-0.268***	-0.053	-0.226***	-0.146***	-0.044	-0.228***	-0.238***	-0.114	-0.234***	-0.142**	-0.098	-0.236***
	(-20.47)	(-3.49)	(-8.03)	(-5.58)	(-1.92)	(-7.36)	(-7.47)	(-0.78)	(-4.35)	(-3.35)	(-0.76)	(-4.62)	(-5.13)	(-1.26)	(-3.33)	(-2.45)	(-1.40)	(-3.74)
IPO_L	-0.032***	0.005	-0.005*	-0.013***	0.014***	0.049***	-0.057***	0.031***	0.000	-0.012***	0.016***	0.042***	-0.058***	0.010	-0.010	-0.012***	0.015**	0.049***
	(-12.14)	(1.47)	(-1.72)	(-8.98)	(7.09)	(23.01)	(-4.83)	(3.27)	(0.01)	(-4.06)	(3.18)	(8.42)	(-3.66)	(0.81)	(-0.99)	(-3.19)	(2.45)	(7.48)
MEAN_EBIT_TA	-0.383***	-0.268***	-0.206***	-0.212***	-0.186***	-0.222***	-0.309***	-0.262***	-0.256***	-0.258***	-0.187**	-0.179**	-0.331***	-0.335***	-0.349***	-0.266***	-0.204**	-0.216**
	(-19.66)	(-8.13)	(-7.47)	(-7.00)	(-5.84)	(-6.93)	(-5.03)	(-3.40)	(-4.12)	(-3.72)	(-2.17)	(-2.22)	(-4.28)	(-2.86)	(-4.12)	(-2.69)	(-2.04)	(-2.02)
MEAN_MB	-0.009***	-0.026***	-0.018***	-0.032***	-0.022***	-0.019***	-0.011*	-0.029***	-0.017***	-0.030***	-0.017**	-0.019***	-0.007	-0.039***	-0.022***	-0.041***	-0.015*	-0.020**
	(-4.34)	(-8.27)	(-7.96)	(-12.93)	(-7.91)	(-6.70)	(-1.83)	(-4.34)	(-3.54)	(-6.00)	(-2.55)	(-2.98)	(-0.87)	(-3.74)	(-3.33)	(-5.74)	(-1.94)	(-2.39)
MEAN_DEP_TA	0.552***	0.371***	0.138	0.081	0.048	0.057	0.386	0.275	0.346	0.311	0.137	-0.085	0.396	0.429	0.463	-0.071	0.410	-0.208
	(7.53)	(3.40)	(1.52)	(0.81)	(0.46)	(0.48)	(1.57)	(1.11)	(1.57)	(1.38)	(0.53)	(-0.32)	(1.29)	(1.21)	(1.60)	(-0.24)	(1.40)	(-0.58)
MEAN_LnTA	-0.010***	-0.009***	-0.016***	-0.015***	-0.007***	-0.009***	-0.005	-0.005	-0.021***	-0.016***	-0.012*	-0.002	-0.012**	-0.017**	-0.019***	-0.016**	-0.005	0.000
	(-6.58)	(-3.88)	(-8.68)	(-7.35)	(-2.99)	(-3.53)	(-1.06)	(-0.97)	(-5.03)	(-3.39)	(-1.89)	(-0.38)	(-2.01)	(-2.21)	(-3.58)	(-2.36)	(-0.70)	(0.06)
MEAN_FA_TA	-0.042***	-0.084***	-0.055***	-0.042**	-0.011	-0.029	0.003	-0.022	-0.017	-0.102***	-0.092**	-0.017	0.061	-0.123*	-0.029	-0.049	-0.130**	0.025
	(-3.98)	(-5.00)	(-3.79)	(-2.57)	(-0.65)	(-1.59)	(0.09)	(-0.50)	(-0.45)	(-2.63)	(-1.99)	(-0.39)	(1.30)	(-1.96)	(-0.57)	(-0.95)	(-2.54)	(0.43)
MEAN_RnD_DUM	-0.009***	-0.010	0.002	0.003	0.006	-0.004	-0.028**	0.019	0.005	-0.017	-0.010	0.007	-0.008	0.032	-0.005	-0.025	0.007	-0.010
	(-2.90)	(-1.58)	(0.30)	(0.46)	(0.90)	(-0.54)	(-2.40)	(1.10)	(0.47)	(-1.18)	(-0.50)	(0.45)	(-0.56)	(1.23)	(-0.33)	(-1.25)	(0.30)	(-0.53)
MEAN_RnD_TA	-0.222***	-0.191*	-0.481***	-0.269***	-0.321***	-0.428***	-0.377**	-0.094	-0.566***	-0.545***	-0.502**	-0.332	-0.129	-0.010	-0.622***	-0.439*	-0.651**	-0.616**
	(-3.47)	(-1.90)	(-5.96)	(-2.97)	(-3.11)	(-3.76)	(-2.19)	(-0.47)	(-3.52)	(-3.03)	(-2.33)	(-1.59)	(-0.62)	(-0.04)	(-2.77)	(-1.81)	(-2.36)	(-2.20)
MEAN_Ind_Median	0.243***	0.111***	0.219***	0.230***	0.089***	0.187***	0.397***	0.069	0.292***	0.288***	0.071	0.217***	0.407***	0.177*	0.280***	0.265***	0.124*	0.175**
	(18.77)	(3.98)	(9.86)	(9.39)	(3.67)	(7.66)	(8.61)	(0.94)	(5.39)	(5.18)	(1.13)	(3.98)	(6.88)	(1.70)	(3.91)	(3.52)	(1.66)	(2.47)
MEAN_IPO	-0.015***	-0.020***	0.030***	0.051***	0.018***	0.015***	-0.015*	-0.037***	0.028***	0.061***	0.002	-0.006	-0.008	-0.032**	0.023***	0.069***	0.001	-0.003
	(-6.36)	(-5.31)	(12.64)	(17.99)	(4.29)	(2.82)	(-1.91)	(-4.17)	(4.87)	(8.93)	(0.17)	(-0.54)	(-0.73)	(-2.38)	(2.89)	(6.80)	(0.09)	(-0.15)
N	42344	13798	14976	17630	9732	13504	3752	2315	3061	3769	1811	2259	2219	1316	1577	2156	1045	1341
*N*_group	5798	3942	4435	4762	3149	3277	747	668	992	1034	593	551	446	394	503	580	343	322
pseudo_R2	0.770	0.761	0.776	0.746	0.774	0.714	0.720	0.765	0.762	0.780	0.793	0.766	0.721	0.767	0.774	0.785	0.830	0.770
sigma_u	0.034	0.034	0.028	0.046	0.042	0.049	0.039	0.029	0.037	0.056	0.044	0.032	0.032	0.057	0.031	0.070	0.031	0.036
sigma_e	0.116	0.115	0.099	0.116	0.083	0.113	0.125	0.116	0.100	0.110	0.086	0.108	0.125	0.109	0.099	0.104	0.083	0.106
rho	0.079	0.080	0.075	0.139	0.204	0.157	0.087	0.057	0.122	0.207	0.207	0.079	0.062	0.212	0.088	0.310	0.123	0.103
speed	0.226	0.132	0.166	0.191	0.237	0.188	0.289	0.153	0.205	0.213	0.201	0.098	0.278	0.262	0.205	0.275	0.141	0.136
Half_Life	3.070	5.236	4.188	3.630	2.922	3.691	2.396	4.543	3.376	3.253	3.450	7.107	2.494	2.650	3.374	2.524	4.912	5.104

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = ln 2/Speed (Years)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

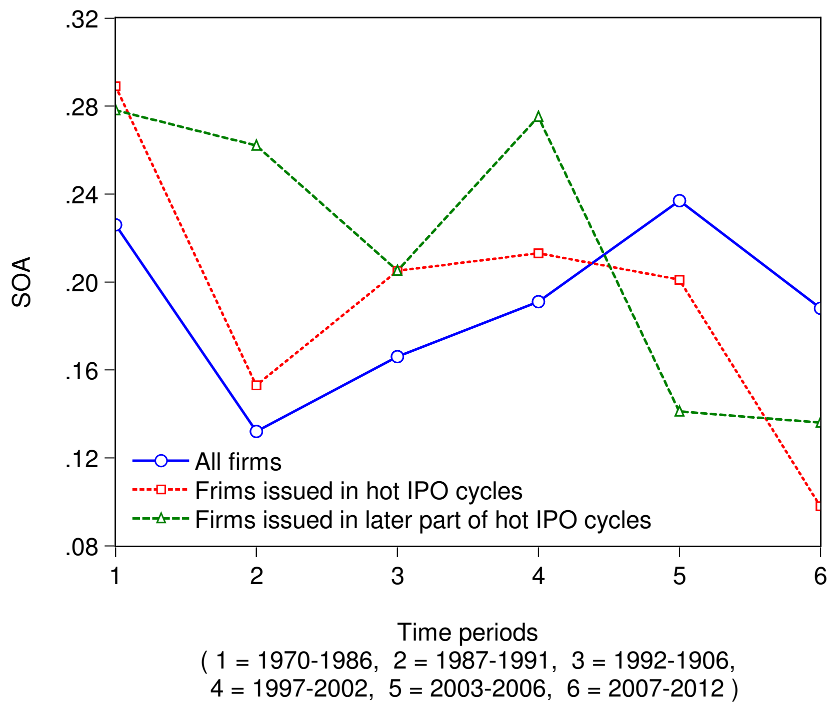


Figure 3.8: Stability over time

This figure shows that the difference in terms of SOA for average firms and firms issued in hot IPO cycles stably exists over time. However, the relation that firms issued in hot cycle always have a higher SOA is not stable. There is a structural change around year 2003, after that, the SOA for average firms are higher than those for firms issued in hot IPO cycles and in later part of hot cycles. See page 66 for more discussions.

Table 3.15: Stability over alternative "leverage" definition

This table summarizes the DPF estimation results using book debt ratio (BDR) as leverage measurement: (1) is for all the firms, (2) is for the firms issued in hot IPO cycles, (3) is for the firms issued in later part of hot IPO cycles. See page 69 for more discussion.

	(1) DPF_ALL_BDR	(2) DPF_Hot_BDR	(3) DPF_Hot_Later_BDR
BDR_L	0.818***	0.787***	0.774***
	(288.08)	(100.26)	(74.53)
FNM_BDR	0.059***	0.071***	0.083***
	(23.04)	(9.84)	(8.26)
EBIT_TA_L	0.041***	0.043***	0.062***
	(10.51)	(4.01)	(4.50)
MB_L	-0.000	-0.001	-0.003*
	(-0.80)	(-1.26)	(-1.91)
DEP_TA_L	-0.179***	-0.164***	-0.119
	(-8.82)	(-2.89)	(-1.60)
LnTA_L	0.001***	-0.003**	-0.002*
	(3.18)	(-2.37)	(-1.79)
FA_TA_L	0.042***	0.057***	0.056***
	(12.31)	(5.58)	(4.24)
RnD_DUM_L	0.001	0.003	-0.001
	(0.67)	(0.83)	(-0.16)
RnD_TA_L	0.069***	0.048	-0.018
	(3.40)	(1.00)	(-0.29)
Ind_Median_L	-0.024***	-0.036***	-0.035**
	(-6.28)	(-2.91)	(-2.14)
IPO_L	0.002***	0.003***	0.002
	(5.25)	(2.59)	(1.34)
MEAN_EBIT_TA	-0.149***	-0.118***	-0.180***
	(-16.78)	(-4.54)	(-5.07)
MEAN_MB	-0.000	-0.003	-0.002
	(-0.62)	(-1.64)	(-0.62)
MEAN_DEP_TA	0.018	-0.011	-0.047
	(0.62)	(-0.13)	(-0.45)
MEAN_LnTA	0.000	0.004***	0.003**
	(0.51)	(3.10)	(2.01)
MEAN_FA_TA	-0.008*	-0.014	-0.013
	(-1.86)	(-1.09)	(-0.80)
MEAN_RnD_DUM	-0.001	-0.007	-0.005
	(-0.49)	(-1.50)	(-0.76)
MEAN_RnD_TA	-0.224***	-0.221***	-0.095
	(-8.83)	(-3.72)	(-1.23)
MEAN_Ind_Median	0.071***	0.109***	0.122***
	(11.81)	(5.93)	(5.06)
MEAN_IPO	-0.003***	-0.009***	-0.009***
	(-3.52)	(-3.91)	(-3.08)
N	114700	17034	9693
N_group	11785	2194	1254
pseudo_R2	0.782	0.774	0.780
sigma_u	0.029	0.041	0.046
sigma_e	0.079	0.085	0.083
rho	0.120	0.188	0.231
speed	0.182	0.213	0.226
Half_Life	3.799	3.255	3.061

t statistics in parentheses; Speed = 1-$b[MDR]$; Half-Life = $\ln 2$/Speed (Years)

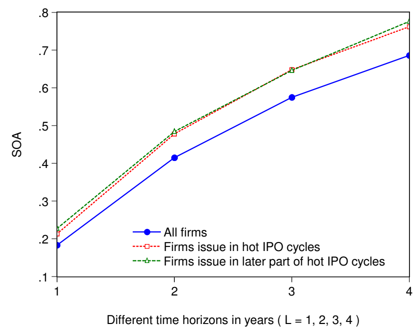
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

firms issued in hot IPO cycles and later part of hot IPO cycles have higher SOA in all four forecast horizons. Fig. 3.9b shows that for all four size groups, the firms issued in hot IPO cycles and later part of hot IPO cycles have higher SOA. Fig. 3.9c shows that the “higher” SOA relation does not always hold throughout the 42 years period, before around year 2003, firms issued in hot IPO cycles and later part of hot IPO cycles have higher SOA, but after that year, the trend reversed.

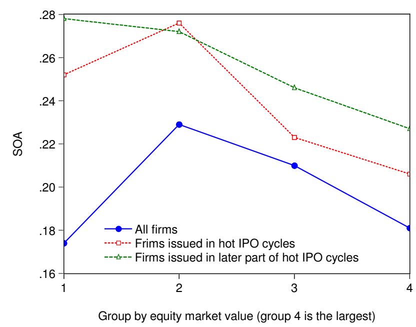
3.5.5 Stability over alternative classification method: S&P 500 firms

In this section, I test whether differences in SOA are robust to alternative classification method. Specifically, instead of issuing in different stages of IPO cycles, classification according to whether a firm is a S&P 500 firm is used. I use the data from Wharton Research Data Services (WRDS) which provides the historical S&P 500 Index constituents. It is located in Compustat, North America, Index Constituents and then search “i0003” for TIC. There are 1,141 unique gvekys for the historical S&P 500 Index constituents from 1970 to 2013, in which 24,514 observations are matched to our data.

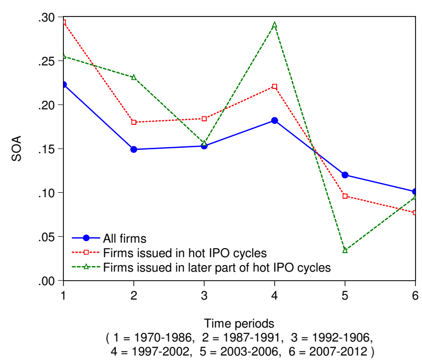
The estimation results are omitted to save space, and can be requested from the author. The key findings, however, are plotted in Fig. 3.10. Fig. 3.10a shows the SOA under different estimation horizons, for all firms, firms issued in hot IPO cycles for all S&P 500 firms, and S&P 500 firms issued in hot IPO cycles in four different forecast horizons. Over all, the SOA is lower for S&P 500 firms, and the difference in SOA between all S&P 500 firms and S&P 500 firms issued in hot IPO cycles is small. Fig. 3.10b shows that for all four size groups, the S&P 500 firms actually have higher SOA for the two size groups in the middle, which is unexpected, and have much lower SOA for the large size S&P 500 firms, which is expected. For S&P 500 firms issued in hot IPO cycles, there is not sufficient firms left in group 2 after grouping by firm sizes,



(a) Stability across different forecast horizons



(b) Stability across firm sizes



(c) Stability over time

Figure 3.9: Robustness check for BDR as leverage measure

This figure summarizes the robustness check result under alternative leverage measure "BDR". Fig. 3.9a shows that under different estimation horizon, firms issued in hot IPO cycles and later part of hot IPO cycles have higher SOA in all four forecast horizons; Fig. 3.9b shows that for all four size groups, the firms issued in hot IPO cycles and later part of hot IPO cycles have higher SOA. Fig. 3.9c shows that the "higher" SOA relation does not always hold throughout the 42 years period, before around 2003, firms issued in hot IPO cycles and later part of hot IPO cycles have higher SOA, but after that year, the trend reversed. See page 69 for more discussion.

therefore its estimation result is missing. Fig. 3.10c shows that S&P 500 firms issued in hot IPO cycles have higher SOA in 1987-1996 and 2007-2012 periods.

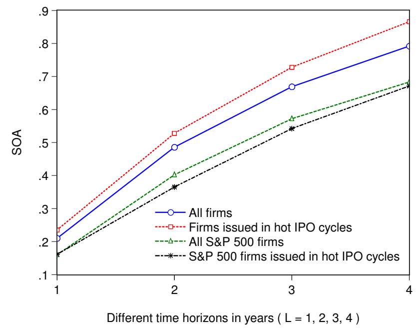
These results show that S&P 500 firms are swift in capital structure adjustments, unless their sizes are too big. In addition, there is a difference in terms of SOA between all S&P 500 firms and the S&P 500 firms issued in hot IPO cycles, and the later group have higher SOA after in the period 1986 to 2012.

3.5.6 Stability over ease of accessing capital markets

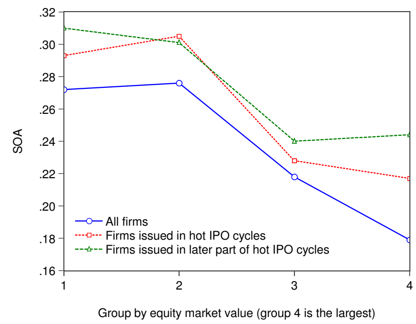
In this section, I will show my finding of difference in SOA is robust over ease of accessing capital markets.

From previous empirical evidence, I find that for small and median sized S&P 500 firms issued in hot IPO cycles have higher SOA, which is consistent with strategic waiting theory. However, one concern is that, this difference may caused by the ease of accessing the capital markets for S&P 500 firms, since most S&P 500 firms issued in hot IPO cycles. If this is the case, excluding the S&P 500 firms from the firms issued in hot IPO cycles, the SOA for the remaining firms should drop, likely below average value. I will check whether those non-S&P 500 firms issued in hot IPO cycle also have higher SOA.

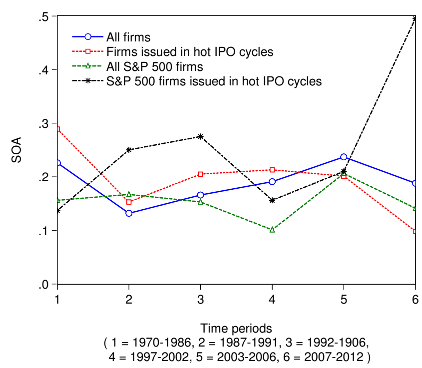
Fig 3.11 summarizes the robustness check results over ease of accessing capital markets. (Again, detailed regression results a omitted to save space, only the SOA of each regression are plotted in the figure.) Fig. 3.11a shows that for all four size groups, the non-S&P 500 firms issued in hot IPO cycles still have higher SOA than average. Fig. 3.11b shows that the non-S&P 500 firms issued in hot IPO cycles have similar patterns with firms issued in hot IPO cycles. The pattern that firms issued in hot IPO cycles have higher SOA is not affect by the ease of accessing capital market for S&P 500 firms. That is, even those firm do not enjoy the advantage of ease of accessing capital market as S&P 500 firms do, they still have much higher SOA than average



(a) Stability across different forecast horizons



(b) Stability across firm sizes



(c) Stability over time

Figure 3.10: Robustness check using S&P 500 firm as a grouping factor

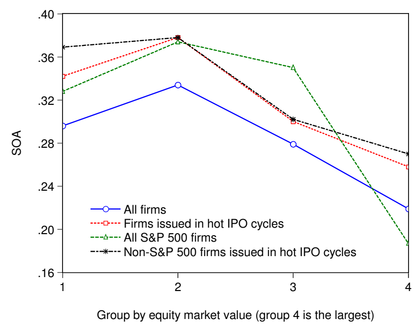
This figure summarizes the robustness check results using S&P 500 firm as a quality indicator. Fig. 3.10a shows the SOA under different estimation horizons, all firms, firms issued in hot IPO cycles for all S&P 500 firms, and S&P 500 firms issued in hot IPO cycles in four different forecast horizons; Fig. 3.10b shows that for all four size groups, the S&P 500 firms actually have higher SOA for the size groups in the middle, and have much lower SOA for the large size S&P 500 firms. Fig. 3.10c shows that S&P 500 firms issued in hot IPO cycles have higher SOA than other groups in the 1987-1996 and 2007-2012 periods. See page 73 for more discussion.

firms.

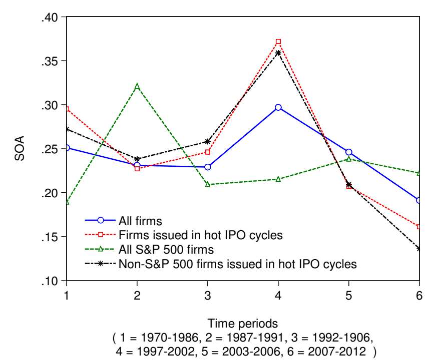
3.6 Summary and conclusions

This chapter studies the relation between strategic waiting behaviors of IPO firms and their subsequent capital structure decisions. By looking into the difference in speed of adjustment towards target leverage ratio of firms went public in different phases of IPO cycles, I find evidence that those firms issued in hot IPO cycles have higher SOA towards target leverage ratios, on average, the SOA is about 12%-260% higher in relatively value (depending on econometric model used), comparing with average firms. I also find on average from year 1970 to 2012, this difference is robust to alternative estimation methods, robust to different estimation horizons, robust to different firm sizes, robust to different time periods, and robust to alternative leverage definition, but from year 2003 to 2012, this relation reversed. I find the difference in SOA for the firms issued in earlier part of hot cycle, and those firms issued later part of hot cycle, is not significant. In addition, I do not find sufficient evidence that the firms issued in later part of hot IPO cycle have different leverage ratios, however, for different age groups, I do find week evidence that firms with age 3, 5 and 7 on average firms issued in hot IPO cycle have a trend to increase its debt leverage over time, which is consistent with strategic waiting theory's prediction.

In sum, there is strong evidence that firms issued in hot IPO cycles are different in terms of adjustment speed of leverage ratio towards targets. There is weak evidence supporting the difference in terms of SOA between firms issued in earlier part of hot cycle and the later part of hot cycle. There is not sufficient evidence supporting that the high and low quality firms differ in debt leverage levels. Nevertheless, for firms in different age groups, there is weak evidence in favor of strategic waiting theory. Previous literature such as Colak and Gunay (2011) mainly concern about the firm performances, this chapter not only provides additional evidence for the strategic waiting



(a) Stability across firm sizes



(b) Stability over time

Figure 3.11: Robustness check for ease of accessing capital markets

This figure summarizes the robustness check results for ease of accessing capital markets. Fig. 3.11a shows that for all four size groups, the non-S&P 500 firms issued in hot IPO cycles still have higher SOA. Fig. 3.11b shows that the non-S&P 500 firms issued in hot IPO cycles have similar patterns with firms issued in hot IPO cycles. See page 75 for more discussion.

theory in a capital structure decision perspective, but also reveals some insights about the relation of a firm's strategic waiting behavior in IPO market and its subsequent capital stricture decisions, and finds that only the speed of adjustment towards the target ratio is positively affected, and the firms waited more patiently during IPO process have higher speed of adjustment. This research also relates to market timing theory by revealing that firms which are more able to timing the market on IPO, also are more quick on capital structure adjustment.

Future research can address two issues raised in this paper. This chapter finds the differences exist in terms of SOA for high and low quality firms, but did not provide an explanation why the differences exist, neither did this chapter explained why before year 2002 high quality firms have higher SOA, and have lower SOA afterwards.

CHAPTER

FOUR

SUMMARY AND CONCLUSIONS

Capital structure is an intensively researched area in finance, many different theories have been proposed in the past, and many more are developing. There is, however, no universal theory can explain all observed facts, and I would not expect to see one (Graham & Leary, 2011). It just like people trying to explain the a trajectory of ball being thrown out, initial theory only considers the gravity and the force applied on the ball, many amendments has been made afterwards, for example to take humility, air resistance, speed and direction of wind, who is throwing the ball and what his/her intention is, etc, into consideration. Moreover, financial problem is more complicated than physical problems, measurement issue, for example, is much harder to deal with in finance. Nevertheless, during the process, many interesting tools in other fields has found their use in financial research (e.g., Markov-switching model in the first essay, DPF estimator in the second essay), and many new tools were invented, which later found their use beyond the initial intentions (e.g., partial-adjustment model in the second essay).

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