Three Essays on External Financing

by

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Abstract

This dissertation consists of three essays in the field of external financing. In Chapter 1, I explore how excess proceeds that arise from the capital-raising process during firms' IPOs affect firms' long-term performance. I document that there are often substantial differences between the filing proceeds and actual proceeds in the initial public offering (IPOs). I refer to the deviation between filing proceeds and issuance proceeds as *excess proceeds*. Using a sample of U.S. IPOs between 1983 and 2017, I further decompose the excess proceeds into 1) market excess proceeds, 2) idiosyncratic excess proceeds and find that the composition of the proceeds affects firms' real activities after IPOs. This evidence highlights the importance of the issuance process when analyzing cash spending behaviors after issuance. Additionally, I examine the implications of excess proceeds for issuers' long-term stock performance. I find that high-excess-proceeds IPOs underperform low-excess-proceeds IPOs by more than 3.6% per year. This study suggests a possible inefficiency in the allocation of proceeds in the IPO book-building process.

Chapter 2 examines the impact of subsequent industry follower IPOs on the long-term stock performance of newly public incumbents. This research is motivated by the recent studies showing that industry peers' IPO decisions exert a negative impact on incumbents' stock performance. We find that industry-followers' IPO decisions account for approximately 60% of NPIs' stock underperformance. Additionally, we show that newly public incumbents with small initial sizes, more growth opportunities, and experience high post-IPO sales and asset growth respond more negatively to industry peers' entry. These results highlight the impact of industry peers' financing decisions on newly public incumbents' stock performance.

Chapter 3 is based on the observation that while SEO withdrawals are rare, many seasoned equity offering (SEO) firms experiencing extremely negative returns over the filing period choose to complete their offerings. We refer to these SEOs as sharp-drop (SD) SEOs and document that managers in SD firms rely more on industry-level and market-level information than on the idiosyncratic information when making the issue/withdraw decision. Also, we find that the SD firms' issuance decision is a defense against delisting. Overall, the evidence suggests that the decision to withdraw is not solely driven by idiosyncratic returns.

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Chapter 1 : Excess Proceeds in the Equity Financing Process

Abstract

Prior work assumes the spending of issuance proceeds from initial public offerings (IPOs) matches perfectly to the firm's motives for equity financing. However, random market fluctuations and information generated during the book-building process can often lead to a difference between the filing and actual issuance proceeds. To address this gap in the literature, I refer to this difference as excess proceeds and document that excess proceeds exhibit substantial cross-sectional variation. These findings have implications for both long-term corporate policies and stock performance. Specifically, I find that the composition of the proceeds affects post-IPO operations, after decomposing excess proceeds into market and idiosyncratic excess proceeds. For example, issuers use market excess proceeds for acquisitions while spending idiosyncratic excess proceeds by expanding existing operations. Moreover, relative to IPOs with low excess proceeds, high-excess-proceeds IPOs' stocks 1) underperform by more than 3.6% per year, 2) are more likely to delist, and 3) are less likely to return for future financing, which suggest that excess proceeds potentially worsen the free cash flow problem (Jensen 1986). Collectively, these findings highlight the impact of the capital-raising process on issuers' long-term performance.

Keywords: Initial public offering, Raising capital, Long-run performance

JEL Classifications: G14, G30, G32

1.1 Introduction

On October 3, 2013, Twitter filed initial public offering (IPO) documents with the U.S. Securities and Exchange Commission (SEC), indicating that it would raise $1 billion worth of primary shares. Despite subsequently announcing a decrease in the anticipated 2013 capital expenditures, on November 7, 2013, Twitter's IPO eventually raised $1.82 billion, nearly doubling the amount it initially intended to raise.[1] Twitter's case is not an isolated incident in the equity issuance market — the differences between the filing proceeds and final proceeds for U.S. IPOs are often large and exhibit economically important cross-sectional variation.[2] Figure 1.1 shows, for example, that 18.4% of IPO issuers receive 25% or more proceeds than initially filed for, while 17.3% of issuers receive 25% or less. These numbers show that the final amount received can deviate from the amount sought at filing, resulting in the final proceeds that are significantly larger or smaller than what the firms intended to raise. In this paper, I refer to the difference between the filing proceeds and the final proceeds as *excess proceeds* and investigate whether these excess proceeds influence firms' post-IPO corporate policies and stock performance.

A growing body of literature shows that firms use issuance proceeds to rebalance capital structure (Pagano, Panetta, and Zingales, 1998; Baker and Wurgler, 2002), relieve short-term liquidity problems (DeAngelo, DeAngelo, and Stulz, 2010), exploit investment

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[1] Twitter cut its anticipated 2013 capital expenditures from 225-275 million on the initial Form S-1 to 215-235 million on the final prospectus.

[2] The filing proceeds are calculated as follows. For example, the filing proceeds of Facebook's IPO are calculated by multiplying $34 (low filing prices) by 180,000,000 (initial filing number of primary shares), which equals $6.12 billion. For issuers such as Twitter, with missing information on the initial filing prices or number of primary shares but available information on the initial filing primary share amount, I first calculate the amended filing proceeds by multiplying the amended low filing price by the number of shares and I choose the minimum between the amended filing proceeds and the initial filing proceeds. I consider only primary shares when calculating proceeds. Please refer to the variable definition section (Section 1.3.1) for more details.

opportunities (Kim and Weisbach, 2008; Hertzel and Li, 2010), increase precautionary cash savings (Mclean, 2011) and finance payouts (Farre-Mensa and Ljungqvist, 2016). While these studies broaden our knowledge of the motives behind equity financing, the current literature exclusively focuses on final proceeds and ignores the fact that issuers do not obtain proceeds upon filings.[3] In contrast, I shed light on the issuance process that can result in sizable deviations in excess proceeds, which in turn substantially alters issuers' post-IPO use of proceeds. This evidence underscores the importance of the issuance process when inferring issuers' motives from the spending of ex-post proceeds. Additionally, excess proceeds arise from price revisions and share revisions. While the extant literature has focused on price revisions during the issuance process (Hanley, 1993; Loughran and Ritter, 2002; Edelen and Kadlec, 2005), I show that the price revisions in prior studies cannot fully account for the excess proceeds.[4] To the extent that excess proceeds directly relate to the total amount of real cash that issuers receive from IPOs, it is important to understand whether and how excess proceeds affect firms' post-issuance decisions.

Excess proceeds can impact long-term corporate policies primarily because managers may perceive excess proceeds as different from filing proceeds. Filing proceeds are disclosed on issuers' filing documents, which reveal crucial information on investment opportunities and the intended use of proceeds, and are reviewed by underwriters to verify the accuracy (Hoberg and Hanley, 2010). Hence, filing proceeds should be a good representation of managers' desired proceeds amount before the issuance process. In contrast, managers are less likely to make their ex-ante investment plans contingent on excess proceeds because they are beyond managers' control: excess proceeds arise from the issuance process, where

[3] Loughran and Ritter (2002) show that on average, it takes 78 days to complete an IPO.

[4] A regression of excess proceeds on price revisions generates an adj-R^2 of 32.84%, which indicates that approximately 67.16% of the variation in excess proceeds cannot be explained by price revisions.

there are fluctuations in random market conditions and idiosyncratic investor demand(Gao and Ritter, 2010; Bernstein, 2015), causing significant price and share revisions. As a result, managers are unlikely to anticipate the magnitudes or even the signs of excess proceeds. Overall, managers should have a more explicit idea of how to utilize filing proceeds than excess proceeds, and may put excess proceeds to different uses.

For my empirical tests, I use 6,295 U.S. IPOs between 1983 and 2017 on the SDC Platinum database and collect information on their filing and issuance dates. I calculate excess proceeds as the difference between filing proceeds and final issuance proceeds. I start by differentiating excess proceeds from price revisions documented in the prior literature. I focus on the comparison between price revisions and share revisions because excess proceeds result from these two revisions. First, by analyzing the frequency of price revisions and share revisions, I find that 55.1% of IPO issuers experience share revisions during the issuance process, indicating that share revisions are not occasional events. Additionally, 20.4% of issuers even adjust shares in opposite directions as price revisions. Second, I explore the determinants of price revisions and share revisions in cross-sectional regressions. I find that issuers can fully adjust shares to favorable market information, which is different from the partial adjustment phenomenon in price revisions.[5] Furthermore, IPO participants such as venture capitalists and underwriters play opposite roles in price revisions and share revisions. Overall, price revisions cannot entirely explain excess proceeds, which necessitates the need to study the excess proceeds.

Next, I examine the impact of excess proceeds on post-IPO corporate policies. Prior studies suggest that random market fluctuations and other idiosyncratic factors such as new

[5] The partial adjustment phenomenon refers to evidence that favorable news is only partially incorporated into the IPO offer prices (Hanley, 1993; Loughran and Ritter, 2002; Edelen and Kadlec, 2005).

information and investor demand during the issuance process can lead to the variation in excess proceeds. Using a market model, I thus further break down excess proceeds into two components: (1) market excess proceeds that are driven by random market fluctuations, and (2) idiosyncratic excess proceeds, which are residuals that reflect idiosyncratic factors during the issuance process. I then follow the methodology in Kim and Weisbach (2008) and investigate the use of filing proceeds, market excess proceeds and idiosyncratic excess proceeds on seven corporate decisions over the course of 1-4 years after IPOs. I include capital expenditures, R&D expenses, cash holdings, acquisitions, debt reductions, share repurchases, and dividend policies that reflect the allocation of IPO proceeds.

I find that the three components play different roles in issuers' post-IPO corporate policies. First, issuers spend filing proceeds and idiosyncratic excess proceeds on capital expenditures and R&D expenses, which is in line with the investment financing explanation of equity financing (Kim and Weisbach, 2008). In contrast, market excess proceeds either are irrelevant or exert a negative impact on investment activities, suggesting that random market fluctuations do not correlate with issuers' ex-ante investment opportunities (Bernstein, 2015). Second, issuers save cash from filing proceeds and idiosyncratic excess proceeds for up to four years after going public while rapidly depleting market excess proceeds. The rapid depletion of market excess proceeds is in line with prior studies that managers may freely squander free cash flows (Jensen, 1986; Harford, Mansi, and Maxwell, 2008). Third, I find that issuers undertake acquisitions and debt reductions using market excess proceeds. Recent evidence suggests that IPO firms demonstrate strong interests in acquisitions (Brau and Fawcett, 2006; Celikyurk et al., 2010), but acquisitions are costly for newly public firms (Brau, Couch, and Sutton, 2012). This evidence indicates that issuers may treat the market excess proceeds as cash windfalls (Blanchard, Lopez-de-Silanes, and Shleifer, 1994). Lastly, I find that issuers tend to pay out filing proceeds as dividends and share repurchases, consistent with issuers “recycling” their equity (Grullon, et al., 2011; Farre-Mensa and Ljungqvist, 2016). Nevertheless, issuers do not disgorge market or idiosyncratic excess proceeds. Taken together, excess proceeds substantially affect issuers’ allocation of IPO proceeds to future corporate activities, which highlights the impact of the issuance process on issuers’ proceeds-spending behaviors.

I perform additional tests for a robustness check. First, I consider underwriters’ impact when decomposing excess proceeds into market and idiosyncratic excess proceeds. Second, issuers may lowball prices to attract investor demand (Lowry and Schwert, 2004), thus driving the relation between idiosyncratic excess proceeds and investments. I mitigate such concern by controlling for high-tech industry issuers because Lowry and Schwert (2004) argue that such issuers may have lowballing filing price incentives. Third, I rule out the alternative explanation that the relation between market excess proceeds and debt reductions merely reflect hot-market IPOs taking advantage of market-timing opportunities to conduct capital rebalancing (Baker and Wurgler, 2002). Following Alti (2006), I control for all hot-market IPOs. Lastly, I further control for IPOs’ founding age to rule out the life-cycle story for issuers’ equity recycling behaviors. The results remain robust.

I then analyze excess proceeds’ implications for long-term stock performance to understand the agency problem behind excess proceeds. The agency problem of free cash flow discussed in Jensen (1986) would predict that issuers receiving excessive cash proceeds may motivate managers to engage in value-destroying activities such as overinvestment at the cost of shareholders, leading to worse long-term stock performance. Conversely, limiting the excess proceeds from the issuance market can discipline managers’ empire building incentives and curb overinvestment (Hertzel, Huson, and Parrino, 2012). Therefore, I expect that IPOs with more excess proceeds should experience worse long-term stock performance.

To test this prediction, each year, I split the IPOs into two groups by excess proceeds and compare their long-term stock performance using the calendar-time portfolio approach. I find that the high-excess-proceeds IPOs underperform the low-excess-proceeds IPOs by 0.30%-0.37% per month, which transforms into 3.60%-4.44% per year. This economically meaningful difference suggests that the excess proceeds potentially aggravate the agency problem of free cash flows and can be detrimental to shareholders in the long term. To alleviate the concerns that investors' overreactions drive the relationship between excess proceeds and long-term poor stock performance, I further split the sample by price revisions and IPO first-day underpricing. Consistent with Hanley (1993), I find no differences in the long-term stock performance between high- and low-price-revision IPOs or between high- and low-IPO-underpricing IPOs, suggesting that excess proceeds have real effects on stock performance through issuers' post-IPO operations. Moreover, by further splitting the high-excess proceeds by the fraction of market excess proceeds, I do not find differences between high- and low-market-excess-proceeds IPOs. This evidence indicates that the market and idiosyncratic excess proceeds equally contribute to long-term stock underperformance.

Lastly, I provide additional evidence that the underperformance of high-excess-proceeds IPOs is driven by future real operations. Specifically, I compare 3-year post-IPO delisting and financing decisions for high- versus low-excess-proceeds IPOs. First, I find that high-excess-proceeds IPOs are associated with higher delisting probability and speed, which is consistent with the prediction that excessive proceeds may incentivize managers to engage in value-destroying activities. Second, issuers can reduce agency costs by frequently returning to the stock market (Easterbrook, 1984). I document that high-excess-proceeds IPOs return to the stock market for future equity financing more slowly, suggesting that excessive excess proceeds reduce managers' demand for future financing and thus disincentivize managers to return to the market and to be monitored by shareholders.

This evidence adds to the literature on the motives for equity financing. Pagano, Panetta, and Zingales (1998) posit that rebalancing capital structure is a more predominant reason for IPOs than financing investment opportunities. In contrast, Kim and Weisbach (2008) attribute Pagano, Panetta, and Zingales' (1998) findings to the old firm age in their Italian IPO sample and assert that financing investments and exploiting overvaluation are the motives for equity financing. Recent literature also uncovers that post-IPO acquisitions strongly motivate managers to go public (Brau and Fawcett, 2006; Celikyurk, Sevilir, and, Shivdasani, 2010). Nevertheless, the current paper shows that acquisitions appear to be driven exclusively by market excess proceeds. To this end, by recognizing the excess proceeds, I show that random market fluctuations and newly generated information during the issuance process affect realized final proceeds, in turn altering issuers' allocation in post-IPO investment activities, acquisitions, and capital rebalancing.

Second, this paper contributes to the debate about whether and why issuers save cash from proceeds. Although DeAngelo, DeAngelo, and Stulz (2010) assert that equity issuers tend to spend the proceeds, Kim and Weisbach (2008), Hertzel and Li (2010) and Mclean (2011) all agree that issuers save cash from proceeds though they cite different reasons. Specifically, McLean (2011) argues that post-issuance cash-savings behavior is due to precautionary motives, while Kim and Weisbach (2008) and Hertzel and Li (2010) posit that managers' market timing behaviors result in cash hoarding. In contrast, this study shows that post-issuance cash-saving activities depend on the different components of the proceeds: issuers tend to save filing proceeds and idiosyncratic excess proceeds, but they deplete market excess proceeds rapidly.

Lastly, this study enriches our understanding of the potential problems in the book-building process. Existing studies have uncovered inefficiency in IPO pricings (e.g., Lowry and Schwert, 2004; Loughran and Ritter, 2002). For example, Loughran and Ritter (2002) document that IPO offer prices do not fully incorporate market information because of underwriters' private incentives to reward affiliated mutual funds and potential investors by underpriced IPOs (Ritter and Zhang, 2007). Additionally, underwriters may have difficulty valuing IPOs when uncertainty is high (Lowry, Officer, and Schwert, 2010). Consequently, Hanley and Hoberg (2010) argue that premarket due diligence can substitute for the costly book-building process. This study shows that excess proceeds are associated with agency problems and that high-excess-proceeds IPOs underperform, which suggests a possible inefficiency in the proceeds allocation in the book-building process: at least some IPOs are allocated funds that may not be effectively utilized after IPOs.

The remainder of the paper is organized as follows. Section 2 provides a discussion about why managers may treat excess proceeds differently from filing proceeds. Section 3 describes the sample and variable constructions. Section 4 reports the empirical results. Section 5 concludes the paper.

1.2 Hypothesis Development

Changes in market conditions and information revealed over the period between filing and issuing securities leads to differences between filing amounts and actual offer proceeds. If managers perceive excess proceeds as different from filing proceeds, the issuance process should ultimately affect the post-issuance use of proceeds.

There are two reasons why managers may treat excess proceeds differently from filing proceeds. First, excess proceeds are beyond managers' control, and thus, managers may not have an explicit idea of how to utilize them. By contrast, filing proceeds should represent the least amount that an issuer requires during IPOs. This definition is in line with Busaba, Liu, and Restrepo (2019), who use low filing prices as a proxy for issuers' reservation prices.

Nevertheless, excess proceeds arise from the issuance process, which is characterized by uncertainty and random market fluctuations (Pastor and Veronesi, 2005; Lowry, Officer, and Schwert, 2010), causing significant revisions in prices and shares, or even completion outcomes (Bernstein, 2015). Given that excess proceeds reflect pure randomness during the issuance process, managers should not rely on excess proceeds to make ex-ante investment plans. Another reason is that filing proceeds should convey more accurate information than excess proceeds on investment opportunities. Underwriters must verify the accuracy of the information on the filing document, Form S-1, which includes potential investment opportunities and the intended use of proceeds. Underwriters and issuers face litigation risk if they mislead investors by using such information (Hanley and Hoberg, 2012). Conversely, excess proceeds are driven by random market fluctuations and idiosyncratic investment demand. Because of the information asymmetry between managers and investors on investment opportunities (Myers and Majluf, 1984), excess proceeds that are driven by investors' perceptions do not necessarily coincide with managers' intended use. Therefore, I expect that excess proceeds alter issuers' post-issuance operations because managers perceive excess proceeds for different uses.

Nevertheless, the issuance process is not purely random because new information is generated during this process (Rock, 1986; Benveniste and Spindt, 1989) and investor demand is created by underwriters (Gao and Ritter, 2010). Therefore, it is necessary to isolate the random portion of excess proceeds from the information portion. Following Bernstein (2015), who documents that filing-period market fluctuations significantly affect IPO completion decisions but are exogenous to ex-ante investment opportunities, I decompose excess proceeds into 1) market excess proceeds, which capture randomness, and

2) idiosyncratic excess proceeds, which capture other idiosyncratic reasons for proceeds adjustments.[6]

I expect that managers treat market excess proceeds as cash windfalls while idiosyncratic excess proceeds relate to post-IPO investment activities because the latter contains information on investment opportunities. However, taken together, I expect that managers utilize filing proceeds better than they utilize either market or idiosyncratic excess proceeds.

1.3 Sample Selection and Variable Definitions

I extract all IPOs from Thomson Reuters SDC with available filing data between 1983 and 2017.[7] Following the IPO sample construction process in Lowry, Michaely, and Volkova (2017), I clean the IPO sample based on the three indicator variables on SDC (IPO_Flag, Original_IPO_Flag, and Issue_Type) and restrict the sample to offerings of common shares, further excluding REITs, ADRs, closed-end funds and limited partnerships. To remain in the sample, an IPO must meet the following criteria: 1) have CRSP and Compustat data, 2) have four-digit SIC codes outside 4900-4999 (utilities) and 6000-6999 (financial firms), 3) have an offer price larger than $1,[8] 4) have securities with share codes 10 or 11, 5) be listed on the NYSE, Nasdaq, or Amex, 6) have completed IPOs within 1 year after filing dates, 7) drop pure secondary offerings, 8) and have pre-IPO total assets that are non-missing and above $1 million. After the above criteria are applied, the sample

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[6] It is worth noting that idiosyncratic excess proceeds may contain idiosyncratic reasons other than the relevant valuation information. For instance, idiosyncratic excess proceeds can be driven by underwriters' lowballing the initial filing price to attract informed investors (Rock, 1986) or pricing-up IPOs to prevent withdrawals when demand is weak (Busaba, Liu, and Restrepo, 2019).

[7] I start in 1983 since IPOs before 1983 do not provide filing information, which is consistent with Lowry, Michaely, and Volkova (2017).

[8] The results are qualitatively similar if I remove IPOs with offer prices below $5.

drops to 7,142 IPOs. Furthermore, I require that an IPO have non-missing excess proceeds. The final sample consists of 6,295 IPOs from 1983 to 2017.

I drop IPOs with SIC codes of 4900-4999 (utility firms) and 6000-6999 (financial firms) because the post-IPO investment and financing activities are different for utility and financial industries. Lastly, I obtain the IPO filing and issuance information from Thomson Reuters SDC platinum. For example, I retrieve variables such as filing amount, total proceeds, offer prices, original file price range, number of primary shares offered, number of primary shares filed, amended primary shares filed, along with other IPO characteristics.

1.3.1 Definitions of Excess Proceeds

I use filing proceeds, which equals the product of the low boundary of the filing price range (*hereafter "LF Price"*) and the number of primary shares filed to proxy for IPO issuers' reservation amount.[9] Some firms do not provide the data needed for computing filing proceeds in the initial filing documents. For example, about 30.11% of issuers in my sample have missing values in initial filing prices or the number of shares. 20.59% of issuers provide primary share amounts but not filing prices or the number of shares on the initial filing documents. For these firms, I follow the prior literature and use data from the first amended filing documents (Lowry, Michaely, and Volkova, 2017).[10] I further require that the filing proceeds calculated from amended filing documents should not exceed the initial filing primary share amounts. Therefore,

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[9] Busaba, Liu, and Restrepo (2019) argue that the low boundary of the filing price range is a valid measure of IPO issuers' reservation prices. Notably, they document that offer prices are discontinuously set at the low boundary of the filing range, which reflects underwriters' incentives to bump up weakly-demanded IPOs to meet issuers' expectations.

[10] It is not mandatory to disclose price and share information on the initial filing dates. Given that the latest amended filing information should be more accurate about information on the final offering, using the amended filing variables on SDC will underestimate the variation in excess proceeds.

$$Filing\,Prcds_i = Min\left[LF\,Price \times \#\,of\,Primary\,Shares, Primary\,Amt\,Filed\right] \tag{1.1}$$

I define excess proceeds as the offered primary share amount minus filing proceeds and scale the excess proceeds by either total assets at t_0[11] or filing proceeds to mitigate the influence of firm size:

$$\frac{Excess\,Proceeds}{Total\,Assets\,or\,Filing\,Proceeds_i} = \frac{Primary\,Amt\,Offered - Filing\,Proceeds}{Total\,Assets\,or\,Filing\,Proceeds_i} \tag{1.2}$$

1.3.2 Decomposing Excess Proceeds

Random market fluctuations and idiosyncratic factors such as newly generated information and investor demand collectively contribute to excess proceeds. First, the extant literature documents that price revisions and completion probability are affected by filing-period market returns, which are regarded as exogenous to issuers' ex-ante investment opportunities (Bernstein, 2015). Moreover, issuers are likely to take advantage of the improved market conditions and sell additional shares to the market, which is consistent with the market timing incentives of equity issuers (Baker and Wurgler, 2002). Second, idiosyncratic information disclosed from the book building process reflects investors' private information about IPO pricings (Benveniste and Spindt, 1989; Edelen and Kadlec, 2005) and contains investment opportunities of which issuers are not aware at the time of IPO filing. Therefore, it is crucial to isolate market excess proceeds from idiosyncratic excess proceeds.

[11] For IPOs after 1997 (when information begins to be available on Edgar), I first use total assets in Compustat prior to the IPOs. For all IPOs, I replace missing values with total assets before IPOs on SDC. If a value is still missing, I replace it with the total assets at the end of the first quarter. Lastly, I replace missing values in total assets at the end of the first fiscal year.

To decompose excess proceeds, I estimate the following regression for IPOs by each year t:

$$\frac{Excess\ Prcds}{Filing\ Prcds}_{i,t} = \alpha_t + \beta_t VW\ Filing\ period\ market\ returns_{i,t} + \varepsilon_{i,t} \tag{1.3}$$

I define the filing period as the period between the filing date and one day before the issuance date. VW filing-period market returns are the cumulative daily market returns. The predicted value, $\widehat{\frac{Excess\ Prcds}{Filing\ Prcds}}_{i,t}$, from the regression above is driven by the filing period market conditions and the residual, ε_{it}, is orthogonal to the market fluctuations and thus reflects idiosyncratic factors. Because Kim and Weisbach (2008) scale total proceeds by total assets, I convert $\widehat{\frac{Excess\ Prcds}{Filing\ Prcds}}_{i,t}$ and $\widehat{\varepsilon}_{i,t}$ by first multiplying filing proceeds and then dividing it by total assets.[12] I refer to the former as market excess proceeds and the latter as idiosyncratic excess proceeds:

$$Market\ Xprcds_i = \widehat{\frac{Excess\ Prcds}{Filing\ Prcds}}_i \times Filing\ Prcds \div Total\ Assets_{i,0} \tag{1.4}$$

$$Idiosyncratic\ Xprcds_i = \hat{\varepsilon}_i \times Filing\ Prcds \div Total\ Assets_{i,0} \tag{1.5}$$

[12] Another reason for using $\widehat{\frac{Excess\ Prcds}{Filing\ Prcds}}_{i,t}$ as the dependent variable is to mitigate the impact of the extreme values of $\widehat{\frac{Excess\ Prcds}{Total\ Assets}}_{i,t}$ on the decomposition regression. Nevertheless, the results are qualitatively similar when $\widehat{\frac{Excess\ Prcds}{Total\ Assets}}_{i,t}$ is decomposed directly.

1.3.3 Summary Statistics

Table 1.1 presents the summary statistics for the 6,295 IPOs. Consistent with the observation from Figure 1.1, excess proceeds exhibit large cross-sectional variation. It is worth noting that $\frac{Excess\,Proceeds}{Total\,Assets_0}$ is positively skewed with a mean of 0.10 and a median of 0. To mitigate concerns related to outliners and the skewness of $\frac{Excess\,Proceeds}{Total\,Assets_0}$, I winsorize the variables at the 1% and 99% levels and follow Kim and Weisbach (2008) to use the logarithmic scale of $\frac{Excess\,Proceeds}{Total\,Assets_0}$ when examining the use of proceeds.[13] Additionally, the means of market and idiosyncratic excess proceeds equal 0.06 and 0.03, indicating that market excess proceeds account for approximately 60% of excess proceeds.

Furthermore, the IPO sample is representative of IPOs in prior studies, although I exclude the financial and utility industries. For example, the average price revisions for IPOs is -1.1%, which is close to the -1.359% in Lowry and Schwert (2004).[14] On average, 42% of IPOs are backed by venture capitalists, which is slightly higher than the 37% in Ritter's (2020) sample. The average IPO underpricing is 18.74%, which is close to the 17.9% found in Ritter (2020).

[13] I also carefully address these outliners in a robustness check (untabulated). I exclude IPOs with absolute values of $\frac{Excess\,Proceeds}{Total\,Assets_0}$ larger than 2.5, offer prices below \$5, and pre-IPO total assets below 5 million. The results remain qualitatively similar. Therefore, the skewness of $\frac{Excess\,Proceeds}{Total\,Assets_0}$ is unlikely to drive the results.

[14] Price revisions vary substantially across samples. For example, the average price revision is equal to -4.3% in Hanley (1993) and 1.9% in Edelen and Kadlec (2005).

1.4 Methodologies and Results

1.4.1 Cross-Sectional Variation of Excess Proceeds

I first examine the magnitude and variation of excess proceeds.[15] Figure 1.1 shows that the variation and magnitude of excess proceeds are non-trivial, where Panel A and B present the histograms of excess proceeds/total assets and excess proceeds/filing proceeds, respectively. It shows that the top-quartile IPO issuers obtain 17.6% (17.4%) more proceeds over filing proceeds (total assets), while the bottom quartile IPO issuers obtain only 83.7% (87.5%) over filing proceeds (total assets). Therefore, the cross-sectional variation in excess proceeds is economically large.

Next, I examine whether the price revisions documented in prior studies can fully account for excess proceeds. Excess proceeds are reflected in the outcome of price revisions and primary share revisions:

$$Excess\,Proceeds = P_0 \times \Delta Shares + \Delta P \times Shares_0 + \Delta P \times \Delta Shares \tag{1.6}$$

where, P_0 and $Shares_0$ are initial filing prices and primary shares, respectively. ΔP and $\Delta Shares$ are revisions in prices and primary shares. An extreme case is that issuers do not adjust the number of shares at all ($\Delta Shares$=0) so that price revisions can entirely explain the variation in excess proceeds. Figure 1.2 presents the frequency distribution of price revisions and share revisions for IPOs. I follow prior studies and define price revisions

[15] Hanley (1993) documents economically sizable price revisions. Notably, she finds that on average, there is a 22.4% decrease (20.9% increase) when offer prices are adjusted downward (upward). As I will show in the following part, there are also sizable revisions in primary shares. Thus, the magnitude and variation of excess proceeds should be large.

as the change from the midpoint of the filing price range to better differentiate excess proceeds from the traditional price revisions measure.

Figure 1.2 reports that primary share revisions do not always change in the same direction as price revisions. For example, only 12.12% of IPO issuers sell the same amount as indicated on the IPO filing documents. When their offer prices were adjusted upward, 9.01% of IPO issuers increase the number of primary shares. Furthermore, 20.37% (6.12%+14.25%) of IPO issuers adjust the number of shares in the opposite directions of price revisions. Regardless of the magnitude in revisions, this evidence seems to be consistent with prior evidence that some issuers may have a specific financing plan before issuance (e.g., Walker and Yost, 2008; Autore, Bray, and Peterson, 2008), such that they choose to stick to a similar amount.

Overall, excess proceeds exhibit a large cross-sectional variation that cannot be explained by price revisions alone. This pattern underscores the need to examine the impact of excess proceeds on the post-IPO use of proceeds.

1.4.2 The Determinants of Excess Proceeds

Figure 1.2 compares the sign changes in price revisions and primary share revisions but neglects the magnitude. To further differentiate excess proceeds from price revisions given in the prior literature, I explore the determinants of price revisions, primary share revisions, and excess proceeds in this section. Specifically, Columns (1)-(2), (3)-(4), and (5)-(6) in Table 1.2 report the determinants of IPO price revisions, primary share revisions, and excess proceeds/filing proceeds, respectively. I include year-by-industry fixed effects and cluster the standard errors by 2-digit SIC industry to remove any time-varying industry shocks. The independent variables are drawn from the previous literature on price revisions.

Column (1) replicates Edelen and Kadlec (2005), and all variables have the same signs and significance level except the VC dummy, which becomes insignificant after including year-by-industry fixed effects.

Table 1.2 reveals that the determinants of price revisions differ from those of primary share revisions. First, the variable filing-period market returns_Neg, which equals filing-period market returns if negative and zero otherwise, captures the asymmetric impact of market returns on price revisions (Edelen and Kadlec, 2005; Lowry and Schwert, 2004; Boeh and Dunbar, 2017)[16]. Filing-period market returns_Neg is insignificant for primary share revisions, suggesting that issuers can fully adjust the offered shares to favorable market information. Second, the VC dummy that equals one for VC-backed IPOs is positive and marginally significant in Column (2), which is consistent with VCs' certification role (Megginson and Weiss, 1991). However, VC is negative and insignificant for primary share revisions, presumably because venture capitalists are indifferent toward issuers' selling primary shares since they will cash out soon. Third, underwriter rankings have a differential impact on price revisions and primary share revisions. Underwriter rankings are positive and significant, which is consistent with the observation that reputable underwriters set initial filing prices more conservatively (Lowry and Schwert, 2004). Alternatively, issuers with proprietary information are more likely to hire reputable underwriters (Boone, Floros, and Johnson, 2016), and rely on the book building process to discover IPO prices and hide valuable information from rivals (Hanley and Hoberg, 2010). However, underwriter rankings are negatively related to the primary share revisions, suggesting that reputable underwriters may prefer that issuers not increase the number of primary shares during the book-building process. Lastly, inconsistent with Corwin and Schulz (2005), I do not find that a larger

[16] Note that Edelen and Kadlec (2005) uses comparable firms returns instead of market returns as independent variable.

syndicate group, which is measured by the number of book runners, plays a significant role in information production during the IPO process. Nevertheless, I find strong evidence that a larger syndicate group is associated with more positive primary share revisions, which is consistent with the marketing role of book runners (Gao and Ritter, 2010).

Next, I turn to the determinants of excess proceeds in Columns (5) and (6). First, filing-period market returns are positive and significant at 1%, indicating that some IPO issuers behave opportunistically: they increase the issuance amount when market conditions improve during the book building process, which can lead to unnecessary issuance proceeds. Second, Ln(filing amount) is negative and significant at the 0.01 level. This evidence suggests that smaller issuers with larger ex-ante uncertainty (Hanley 1993) tend to increase the offered amount as their uncertainties are resolved during the IPO process. Third, Columns (1)-(4) document the differential impact of reputable underwriters on price revisions and changes in the number of primary shares. The positive and significant coefficients of underwriter rankings in Columns (5)-(6) show that IPOs with reputable underwriters are more likely to adjust proceeds upward. Lastly, share overhang, which is the unsold proportion of outstanding shares in IPOs (Bradley and Jordan, 2002; Boeh and Dunbar, 2016), is positive and significant at 1%, suggesting that issuers with more retained shares are more likely to increase the selling amount.

1.4.3 Use of IPO Proceeds

In this section, I explore the relationship between excess proceeds and post-issuance activities. I hypothesize that issuers put the three portions of cash proceeds – filing proceeds, market excess proceeds, and idiosyncratic excess proceeds – to different uses. Following Kim and Weisbach (2008), I use only primary share proceeds, namely, the funds go to firms instead of insiders. I split the three portions of cash proceeds and follow the use of proceeds regressions in Kim and Weisbach (2008):

$$
\begin{aligned}
Y_t = {} & \beta_1 \ln\left[\left(\frac{Filing\ Prcds}{Total\ Assets_0}\right)+1\right] + \beta_2 \ln\left[\left(\frac{Mkt\ Xprcds}{Total\ Assets_0}\right)+1\right] + \\
& \beta_3 \ln\left[\left(\frac{Idsyn\ Xprcds}{Total\ Assets_0}\right)+1\right] + \beta_4 \ln\left[\left(\frac{Other\ Sources}{Total\ Assets_0}\right)+1\right] \\
& +\beta_5 \ln\left[Total\ Assets_0\right] + Year \times Industry\ F.E. + \varepsilon
\end{aligned}
\tag{1.7}
$$

where $Y = \ln\left[\left(\frac{V_t - V_0}{Total\ Assets_0}\right)+1\right]$ for V=cash, and $Y = \ln\left[\left(\frac{\sum_{i=1}^{t} V_i}{Total\ Assets_0}\right)\right]$ for V= capital expenditures, acquisitions, R&D expenses, reductions in long-term debt, dividend payments or share repurchases.[17] Other sources in the regression are defined as $\ln\left[\left(\sum_{i=1}^{t}\frac{Total\ Source\ of\ Funds_i - Primary\ Proceeds}{Total\ Assets_0}\right)+1\right]$, where t=1 to 4 years after IPOs.

Table 1.3 presents the use of proceeds regressions for IPOs. Consistent with this prediction, IPO issuers put the three portions of cash proceeds to different uses. First, post-IPO cash changes are related to filing proceeds and idiosyncratic excess proceeds in all four-year regressions. Interestingly, cash changes are not correlated with market excess proceeds, indicating that issuers deplete market excess proceeds more rapidly than the other two portions.

Second, turning to the post-IPO capital expenditures and R&D spending regressions, both filing proceeds and idiosyncratic excess proceeds are positive and significant at 1%.

[17] Dividend payments and share repurchase are not in Kim and Weisbach (2008). However, Farre-Mensa, Michaely, and Schmalz (2017) argue that firms may issue equity to payout. I include these two variables in the regressions.

The highly significant filing proceeds lend further support to the investment financing explanation in Kim and Weisbach (2008), revealing issuers' intent to exploit investment opportunities at the time of IPO filing. Furthermore, market excess proceeds are irrelevant to investment activities or even negatively related to R&D expenses in years 3 and 4. Thus, random market fluctuations during the book-building process do not contain information on post-IPO investment opportunities.

Third, market excess proceeds are positively associated with post-issuance acquisitions in years 2-4 (marginally significant in year 4), while neither filing proceeds nor idiosyncratic excess proceeds are significant. The previous literature shows that acquisitions conducted by newly public firms are very costly and reflect managers' empire building incentives (Brau, Couch, and Sutton, 2012); thus, spending IPO proceeds on acquisitions may destroy shareholders' values, which is consistent with the agency problems in cash windfalls in Blanchard, Lopez-de-Silanes, and Shleifer (1994).

Fourth, market excess proceeds are positive and significant for the long-term debt reduction regressions from years 1-3, while the filing proceeds are negatively significant in years 2-4. Additionally, idiosyncratic excess proceeds remain negatively significant for all 4-year regressions. This evidence echoes Hertzel and Li's (2011) finding that equity issuers may replace debt with cheaper equity.

Lastly, filing proceeds are positive and significant at 1% for dividends and share repurchase policies in all four years, which is consistent with the notion that issuers "recycle" their payouts (Grullon, et al., 2011; Farre-Mensa and Ljungqvist, 2016). Nevertheless, neither market nor idiosyncratic excess proceeds are significant for IPO issuers' payout policies. These results suggest that issuers do not disgorge excess proceeds, which could potentially aggravate the agency problem of free cash flows.

In terms of the economic significance, I find that a 1-standard-deviation increase in $\ln\left[\left(\frac{Mkt\ Xprcds}{Total\ Assets_0}\right)+1\right]$ is associated with a \$5.2 million increase in post-IPO acquisitions, and a \$69.2 million increase in debt reductions for the first two years.[18] These numbers are economically meaningful given that the total amount of acquisitions and debt reductions two years after IPOs are \$23.7 million and \$99.3 million, respectively. Additionally, a 1-standard-deviation increase in $\ln\left[\left(\frac{Idsyn\ Xprcds}{Total\ Assets_0}\right)+1\right]$ are associated with a \$9.9 million increase in capital expenditures and a \$13.4 million increase in R&D expenses, compared to average amounts of \$51.7 million in capital expenditures and \$192.8 million in R&D expenses for the first 2 years. Collectively, excess proceeds substantially affect the post-IPO use of proceeds.

1.4.4 Underwriters' Impact on the Use of Proceeds

Prior IPO literature suggests that underwriters also contribute to the IPO price discovery process. For example, issuers with weaker bargaining power than underwriters can be more subject to underwriters' pressure to incorporate favorable market information (Willenborg, Wu, and Yang, 2015). By simply splitting excess proceeds by filing-period market returns and year in Equation (1.3), I may underestimate market excess proceeds and overestimate idiosyncratic excess proceeds. To better control underwriters' influence on

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[18] I focus on year 2 because market excess proceeds firms start going to acquisitions in year 2. I use the mean of total assets in year 2, \$192.8 million, as pre-IPO total assets. For example, the coefficient of standardized $\ln\left[\left(\frac{Mkt\ Xprcds}{Total\ Assets_0}\right)+1\right]$ equals 0.019, which indicates that a 1-standard-deviation increase in $\ln\left[\left(\frac{Mkt\ Xprcds}{Total\ Assets_0}\right)+1\right]$ results in a 0.019 increase in $\ln\left[\left(\frac{\sum_{t=1}^{2} Acquisitions_i}{Total\ Assets_0}\right)+1\right]$. It transforms into a \$5.2 million increase in acquisitions in the first 2 years.

market excess proceeds and idiosyncratic excess proceeds, I first split all IPOs into terciles based on underwriter rankings and then reestimate Equation (3) by year and by underwriter ranking terciles. Table 1.4 shows that the results are qualitatively similar to those in Table 1.3.

1.4.5 Robustness Check

1.4.5.1 Price-Lowballing Incentives

Prior studies suggest that the initial filing prices may not be an unbiased estimator of issuers' intrinsic values (Lowry and Schwert, 2004).[19] For example, issuers may lowball initial filing prices to attract investor demand to disclose private information (Rock, 1986; Benveniste and Spindt, 1989). Accordingly, underwriters with strong bargaining power may exert pressure on issuers to suppress prices (Liu and Ritter, 2011). In this case, idiosyncratic excess proceeds may contain information that is endogenous to ex-ante investment opportunities. Hence, the positive relationship between idiosyncratic excess proceeds and post-IPO investment activities may reflect only price-lowballing behaviors.

To mitigate this concern, I reestimate regression (1.7) in Table 1.5 by including a dummy variable, Htech, which equals one for IPOs within high-technology industries and captures issuers' price-lowballing incentives. Specifically, Lowry and Schwert (2004) argue that IPOs within high-technology industries (e.g., biotech or computer equipment industries) are more likely to lowball initial filing prices. If the price-lowballing behavior is the primary reason, we should expect the positive relation between idiosyncratic excess proceeds and post-IPO investment activities to be absorbed by the Htech dummy. Note that price-

[19] Though Lowry and Schwert (2004) show that the bias of using initial filing prices as a predictor for offer prices is not economically meaningful.

lowballing behavior should not influence market excess proceeds because it captures the random market fluctuations during the issuance process.

1.4.5.2 Hot-Market IPOs

Prior literature also shows that equity issuers may take advantage of market timing opportunities and rebalance capital structure after IPOs (Baker and Wurler, 2002). Hence, one concern is that the negative relation between long-term debt reductions and market excess proceeds may merely reflect the fact that issuers do IPOs during a hot market. It is worth noting that market excess proceeds capture post-filing market fluctuations, which are different from the general market conditions measured in years or months as in prior studies. Additionally, Alti (2006) show that the market timing impact on capital structure rebalancing is not persistent for hot-market IPOs: their leverage ratios become indistinguishable from those of cold-market IPOs within two years after IPOs. Therefore, it is unlikely that the hot market phenomenon will entirely drive the results between market excess proceeds and post-IPO debt reductions.

To alleviate the concern regarding the hot-market impact on the negative relation between debt reduction and market excess proceeds, I add a dummy variable, HotMkt, to measure hot-market IPOs. Specifically, following Alti (2005), I use the SDC sample before dropping the financial and utility industries to determine the number of IPOs for each month. I then take a 3-month centered moving average over 1983-2017 for each month. I define hot-market IPOs as those falling in the top quintile in the distribution of 3-month IPO volume.[20]

[20] The correlation between HotMkt dummy and market excess proceeds is 0.03.

1.4.5.3 Life-Cycle Story and Payout Policies

The life-cycle story of payout policies predicts that mature firms should pay out more because of their higher profitability and that they have fewer investment opportunities. For example, Fama and French (2001) shows that the recent disappearing dividends phenomenon can be explained by the changing characteristics of publicly traded firms. DeAngelo, DeAngelo, and Stulz (2006) documents that firms with relatively larger retained earnings over contributed capital strongly determine the probability of dividends payout policy.

If mature issuers tend to file larger amount of proceeds, then a potential endogeneity is that the positive relation between filing proceeds and future payout policies is driven by issuers' life cycle stages. To mitigate this concern, I include founding age that measures the age when an IPO issuer goes public into the regression.[21]

1.4.5.4 Results

Table 1.5 summarizes the results. First, idiosyncratic excess proceeds remain positive and significant for cash savings, capital expenditures, and R&D expenses, suggesting that the use of idiosyncratic excess proceeds in Table 1.3 is not driven purely by issuers' incentives to lower initial filing prices. Additionally, the dummy variable, HotMkt, does not absorb the positive relation between the long-term debt reduction and market excess proceeds. Lastly, controlling for issuers' life cycles does not affect the results of payout policies. Overall, the results show that the price-lowballing behaviors, hot market phenomenon, and life-cycle story cannot fully account for the evidence in Table 1.3.

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[21] The founding age is calculated by a firm's IPO year minus the founding year. I thank Professor Jay Ritter for the founding dates that he provides at:
https://site.warrington.ufl.edu/ritter/files/2019/05/FoundingDates.pdf

1.4.6 Additional Tests

1.4.6.1 Use of the Over-allotment Option Amount

The over-allotment (or Green-shoe) option allows underwriters to sell up to 15% of issuers' shares at the offer price within 30 days following IPOs. Once exercised, it increases issuers' primary shares, which eventually increase issuers' total proceeds. Therefore, I also examine how IPO issuers spend the proceeds from underwriters' exercise of over-allotment options. I summarize the results in Table 1.6 by adding a sixth variable, $\ln\left[\left(\frac{Overallotment\ Option}{Total\ Assets_0}\right)+1\right]$, which describes the use of the over-allotment option amount.[22] Table 1.6 shows that issuers tend to save this amount until 4 years after IPOs and spend it on capital expenditures and R&D expenses. However, issuers do not utilize the over-allotment amount to engage in debt reduction and post-IPO acquisitions. Lastly, the over-allotment amount is positive and significant in years 3 and 4 for share repurchases, indicating that issuers tend to return this amount to shareholders in the future.

Nevertheless, the results in Table 1.6 should be interpreted with caution. First, Dambra, Gustafson, and Pisciotta (2019) suggest that the over-allotment on Thomson Reuters SDC is noisy, where SDC occasionally reports missing values in overallotment amounts even when underwriters indeed exercise the overallotment option. Second, if the market price after IPO is below the offer price, underwriters may buy back shares from the secondary market to stabilize prices. In this case, we cannot determine the precise number of shares from the exercise of the over-allotment option.[23]

[22] For IPOs without an over-allotment options, I set the over-allotment option amount to zero.

[23] As confirmed by the Thomson Reuters SDC customer support, the over-allotment option amount does not exclude the amount that underwriters buy back because the buy-back amount is post-deal activities.

1.4.6.2 Use Linear Scale for Market and Idiosyncratic Excess Proceeds

The main results in Table 1.3 use the logarithmic scale of market and idiosyncratic excess proceeds to mitigate the skewness in $\frac{Excess\ Proceeds}{Total\ Assets_0}$. A problem is that 282 IPOs with either market or idiosyncratic excess proceeds smaller than -1 are automatically dropped from the estimation. To rule out the possibility that these 282 IPOs might affect my results, I include these IPOs without using a logarithmic scale in the appendix (Table 1.A3). The results are robust after I include these 282 IPOs.

1.4.7 IPO Long-run Stock Performance

Recent literature has examined the impact of post-issuance real activities on issuers' stock performance. For example, prior studies document that post-issuance investment (Carlson, Fisher, and Giammarino, 2004; Titman, Wei, and Xie, 2004; Lyandres, Sun, and Zhang, 2008), follow-on financing (Billett, Flannery, and Garfinkel, 2011), acquisitions (Brau, Couch, and Sutton, 2012) and frequent large equity and debt issues (Huang and Ritter, 2018) can contribute to issuers' long-term stock underperformance. Likewise, excess proceeds affect issuers' proceeds spending behaviors and may thus predict issuers' long-term stock performance. Specifically, excessive cash proceeds may incentivize managers to overinvest or engage in other value-destroying activities. Conversely, agency costs can be restricted by limiting managers' access to excess cash. Therefore, I expect that relative to low-excess-proceeds IPOs, high-excess-proceeds IPOs exhibit worse long-term stock performance.[24]

[24] Accordingly, issuers who receive insufficient proceeds may have to cancel the optimal project and yield to the suboptimal project, resulting in value-losses. This possibility will bias against finding any differences in the long-term stock performance.

However, because excess proceeds are a function of price revisions, this evidence could also be consistent with the investor overreaction hypothesis in Ritter (1991). Specifically, this hypothesis attributes long-term stock underperformance to short-term IPO overpricing and thus predicts that optimistic investors' overreaction to IPOs leads to a negative relation between price revisions and long-term stock performance. However, Hanley (1993) fails to find a significant relation between price revisions and initial returns, casting doubt on the investor overreaction hypothesis. To further alleviate this concern, I also examine whether price revisions and IPO first-day underpricing can predict the IPO long-term stock performance.

Following Mitchell and Stafford (2000), I use the 3-year calendar-time portfolio approach to examine the long-term stock performance of high- and low-excess proceeds. To avoid any look-ahead bias, each year, IPOs are split into high- and low-excess-proceeds groups based on the medians of either $\frac{Excess\ Proceeds}{Total\ Assets_0}$ or $\frac{Excess\ Proceeds}{Filing\ Proceeds_0}$ from year t-10 to t-1.[25] I split the sample by year to mitigate the influence of time-varying factors on excess proceeds. Following the methodology in Loughran and Ritter (2000), I construct purged Fama-French three factors and a purged investment factor to avoid contamination problems by recent IPO and SEO issuers. Furthermore, I construct long-short portfolios that long the high group and short the low group to compare the alpha differences.[26]

[25] IPOs in year 1983 (the first year in my sample) are thus not used. Using a long horizon generates more stable medians over the years. However, the results are robust if spitting IPOs by the medians between year t-3 to t-1, or by the median of year t (including year 1983).

[26] Following Shumway (1997), I correct the survivorship bias in the event portfolio. Specifically, if an IPO delists before the third calendar year and if its delisting return is available on CRSP, I include its delisting return. If the delisting return is unavailable, I include the delisting returns by examining the reasons for delisting. If DLSTCD is 500, 520, between 551 and 571, 574, 580 or 584, I take the delisting returns as -30%. If the DLSTCD has other values, I take the delisting return as -100%.

Panel A shows that splitting by $\frac{Excess\ Proceeds}{Total\ Assets_0}$ yields alphas equal to -0.488% and -0.187% for high and low groups, respectively. Importantly, the high-excess-proceeds group significantly underperforms the low-excess-proceeds group (p-value: 0.02) by -0.306% per month, which transforms into -3.672% annual returns. This finding is economically significant compared to the evidence that IPOs underperform by -7.1% in three years after IPOs (Ritter 2011). Additionally, this result remains robust after the purged investment factor is added (p-value: 0.01). Likewise, Panel B shows that splitting the IPO sample by $\frac{Excess\ Proceeds}{Filing\ Proceeds_0}$ yields the same results.

Panel C in Table 1.7 presents the results of splitting by price revisions. With purged Fama-French three factors, α is equal to -0.294 and -0.343 for the high- and low-price-revision groups, respectively.[27] However, the α difference is insignificant from zero (p-value: 0.67), which is consistent with Hanley's (1993) finding that price revisions cannot predict IPO long-term stock performance. Similarly, Panel D shows that splitting IPOs by the first-day underpricing does not generate significant α differences (p-value: 0.76). Therefore, the α differences between high- and low-excess-proceeds groups are more related to post-IPO spending behaviors (e.g., Titman, Wei, and Xie 2004; Brau, Couch, and Sutton, 2012) instead of price reversals from short-term pricings.

To examine whether market or the idiosyncratic excess proceeds account for the underperformance, I retain the high-excess-proceeds group and further split it by $\frac{Market\ Excess\ Proceeds}{Idiosyncratic\ Proceeds}$ in each year. Panels E and F show that α do not differ significantly

[27] Note that one difference between Hanley (1993) and this study is that she splits the IPO sample by positive, negative and zero price revisions. Instead, I sort the IPO sample by each year to better control for the variation in calendar years.

for high versus low $\frac{Market\ Excess\ Proceeds}{Idiosyncratic\ Proceeds}$ groups, suggesting that market and idiosyncratic excess proceeds equally contribute to the underperformance of high-excess-proceeds group.

Taken together, excess proceeds affect issuers' real operations; thus, excess proceeds can predict issuers' long-term stock performance.

1.4.8 Three-Year Post-IPO Delisting Decisions

To further determine how the long-term underperformance of the high-excess-proceeds group is driven by the real impact of excess proceeds, I explore post-IPO delisting decisions. I hypothesize that high-excess-proceeds IPOs are more likely and delist more rapidly.

First, I estimate the 3-year probabilities of delisting and being acquired in the probit model. Specifically, I classify delisting and being acquired by CRSP delisting codes between 300 and 599 ("Exchanges, Liquidations, and Dropped") and between 200 and 299 ("Mergers"), respectively. I estimate the following regression with year and industry fixed effects and cluster the standard error by industry:

$$D\left(Delist\ or\ Acq_{i,j,t+3}\right) = \beta\left(High\frac{Xprcds}{TotalAssets}_{i,j,0}\ or\ \frac{Xprcds}{FilingPrcds}_{i,j,0}\right) + Controls_{i,j,t} + \gamma X_{j,t} + \varepsilon \quad (1\text{-}8)$$

If an IPO firm delists or is acquired within 3 years after its IPO, the dependent variable, $D(Delist\ or\ Acq_{i,j,t+3})$, is assigned a value of one. Additionally, following Section 1.4.7, I define $High\frac{Xprcds}{TotalAssets}_{i,j,0}$ and $High\frac{Xprcds}{FilingPrcd}_{i,j,0}$ as dummy variables equal to one if an IPO belongs to the high-excess-proceeds group in year t. I expect β, which are the coefficients of $High\frac{Xprcds}{TotalAssets}_{i,j,0}$ and $High\frac{Xprcds}{FilingPrcd}_{i,j,0}$, to be positive and significant, indicating that high-excess-proceeds IPOs are more likely to delist after the IPO.

Table 1.8 shows that both $High\frac{Xprcds}{TotalAssets}_{i,j,0}$ and $High\frac{Xprcds}{FilingPrcd}_{i,j,0}$ are positive and significant in Columns (1) and (2), which is consistent with the prediction that high-excess-proceeds IPOs are more likely to delist. Being in the high-excess-proceeds group increases the probability of delisting by 1.251% and 1.026%, respectively. These results are economically significant compared to the average delisting probability of 7.911% of the full sample. However, I do not find that high-excess proceeds IPOs are more likely to be acquired after IPOs (Columns (3) and (4)). Additionally, I include year-by-industry fixed effects to further remove time-varying industry shocks and I accommodate these fixed effects in a linear probability model. The results in Columns (5)-(8) are consistent with those in the probit model.

Second, I analyze whether excess proceeds affect the speed of delisting and being acquired in a hazard model. If high excess proceeds are related to future poor performance, we should observe that IPOs with high excess proceeds delist faster. I use quarterly data to assess the effect of excess proceeds on the 3-year survival probability in a Cox proportional hazard model. Methodologically, this model estimates the probability of delisting in quarter q, conditional on the firm not delisting from the stock market in quarter q-1. Specifically, I estimate the hazard rate for IPOs' delisting decisions as follows:

$$h\left(q\right) = h_0\left(q\right)exp\left[\left(High\frac{Xprcds}{TotalAssets}_{i,j,0}\ or\ \frac{Xprcds}{FilingPrcds}_{i,j,0}\right) + Controls_{i,j,q} + \gamma X_t + \eta Z_j + \varepsilon\right] \tag{1-9}$$

where q is the length of the duration; $h_0(q)$ is the baseline hazard, which is obtained by setting all other explanatory variables to zero; and β is the interested coefficient. If high-excess-proceeds IPOs delist or are acquired more rapidly 3 years after IPOs, the hazard ratio of β should be larger than 1. Table 1.9 summarizes the results. Columns (1) and (2) show that both $High\frac{Xprcds}{TotalAssets}_{i,j,0}$ and $High\frac{Xprcds}{FilingPrcd}_{i,j,0}$ dummy variables are statistically significant at 0.01 for delisting decisions, with a magnitude larger than 1, suggesting that high-excess-proceeds IPOs delist more rapidly than low-excess proceeds IPOs.

1.4.9 Three-Year Post-IPO Financing Decisions

Prior literature shows that returning to the stock market frequently restricts managers' agency problems of spending free cash flows (Easterbrook, 1984). Specifically, Hertzel, Huson, and Parrino (2012) document that investors provide equity capital in stages to mitigate the costs associated with managers' overinvestment behaviors. If raising excessive proceeds disincentivizes managers from returning to the market and being monitored by shareholders in the future, it may exacerbate the free cash flow problem. Therefore, another mechanism for the underperformance of high-excess-proceeds IPOs is that these IPOs decelerate their pace of future equity financing.

I use the definitions of equity and debt financing in McKeon (2015) and Huang and Ritter (2018). Specifically, an IPO firm is defined to have an equity issue or debt issue in one quarter if the net equity amount or net debt amount is at least 5% of the book value of the asset and at least 3% of the market value of equity. This criterion contains both future private and public equity financing and excludes the impact of executives' exercise of stock options. All issue is defined as either an equity issue or a debt issue in a quarter. To be consistent with the delisting section, I truncate the sample until 3 years after firms'

IPOs. Moreover, I allow repeated events to occur in this section because firms' future financing activities are more frequent than firms' delisting activities. As a result, the remaining observations of a firm are retained after this firm conducts external financing.

Columns (1) and (2) in Table 1.10 show that $High\frac{Xprcds}{TotalAssets}_{i,j,0}$ and $High\frac{Xprcds}{FilingPrcd}_{i,j,0}$ dummies are both significant at 0.01 and that the hazard ratios are below 1, suggesting that IPOs with more excess proceeds are 16.3% (1-0.837) and 17.5% (1-0.825) less likely to return to the market for future equity financing. In contrast, excess proceeds appear to be less related to future debt financing. Column (3) shows that $High\frac{Xprcds}{TotalAssets}_{i,j,0}$ is significant at 0.05, while $High\frac{Xprcds}{FilingPrcd}_{i,j,0}$ remains statistically insignificant (p-value: 0.47). Additionally, the economic magnitude for debt financing is much smaller. Column (3) suggests that IPOs with more excess proceeds are 6.7% less likely for future debt financing.

1.5 Conclusion

Prior studies seek to understand the motives for equity financing by examining the post-issuance use of proceeds, but the evidence is mixed. One limitation is that existing studies generally assume homogeneity in proceeds and ignore the influence of the capital-raising process on final issuance proceeds. In this study, I examine the impact of the issuance process on total proceeds by partitioning total proceeds into two parts: 1) filing proceeds that serve as issuers' reservation amount before the offerings are completed, and 2) excess proceeds that reflect random market fluctuations and other idiosyncratic factors during the issuance process. I show that excess proceeds arising from the issuance process exhibit substantial cross-sectional variation among issuers, which cannot be explained solely by revisions in offer prices. I further break down excess proceeds into market excess proceeds and idiosyncratic excess proceeds and find evidence that issuers tend to spend the three components in different ways. For example, issuers tend to treat market excess proceeds as cash windfalls while spending idiosyncratic excess proceeds on capital expenditures and R&D expenses. Furthermore, these results are unlikely to be explained by price-lowballing incentives, the hot market phenomenon, or the life-cycle story of payouts. These findings suggest that the capital-raising process can deviate issuers from their initial motives for equity financing.

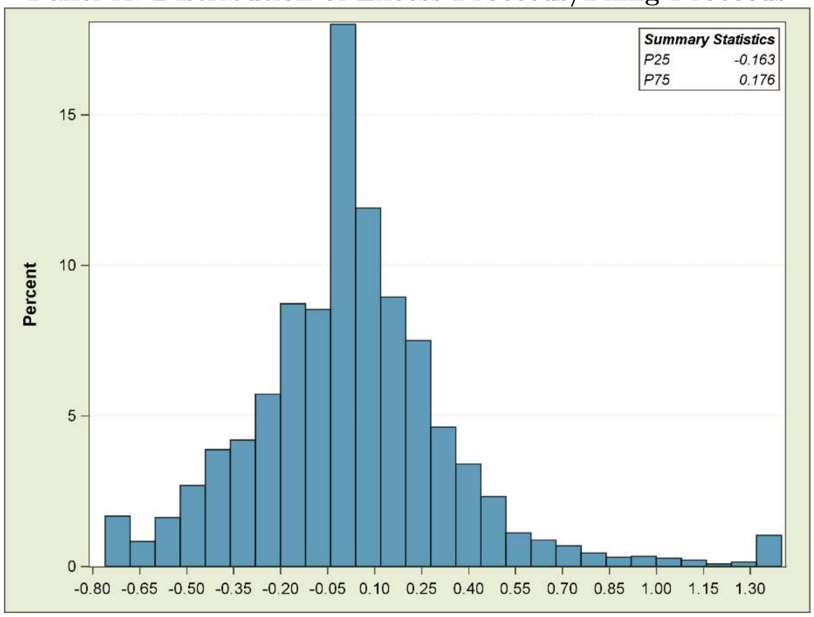
I further show that excess proceeds have implications for issuers' long-term stock performance. Relative to that of low-excess-proceeds IPOs, the stock of high-excess-proceeds IPOs stock tends to underperform by more than 3.6% per year. Additional evidence shows that high-excess-proceeds IPOs are more likely to delist in the future. Lastly, high-excess-proceeds IPOs are less likely to return to the stock market for future equity financing, which potentially aggravates the free cash flow problems discussed in Jensen (1986).

To the extent that IPO issuers use market excess proceeds for costly acquisitions and high-excess-proceeds IPOs underperform more, this study suggests a possible inefficiency of capital allocation in the IPO book building process. Overall, this paper highlights the real impact of the random market fluctuations and other idiosyncratic reasons on issuers' long-term proceeds spending and stock performance

Figure 1.1: Histogram of IPO Excess Proceeds

This figure shows the histograms of excess proceeds for U.S. IPOs between 1983 and 2017. Panels A and B present excess proceeds/filing proceeds and excess proceeds/total assets, respectively. Filing proceeds are the product of the low filing price and the initial filing number of primary shares. Whenever the initial filing price or filing number of shares is unavailable, I use information on the amended filing documents and require that this number is no larger than the initial filing primary share amount. The x axis represents excess proceeds and the y axis represents the percentage.

Panel A: Distribution of Excess Proceeds/Filing Proceeds



Panel B: Distribution of Excess Proceeds/Total Assets

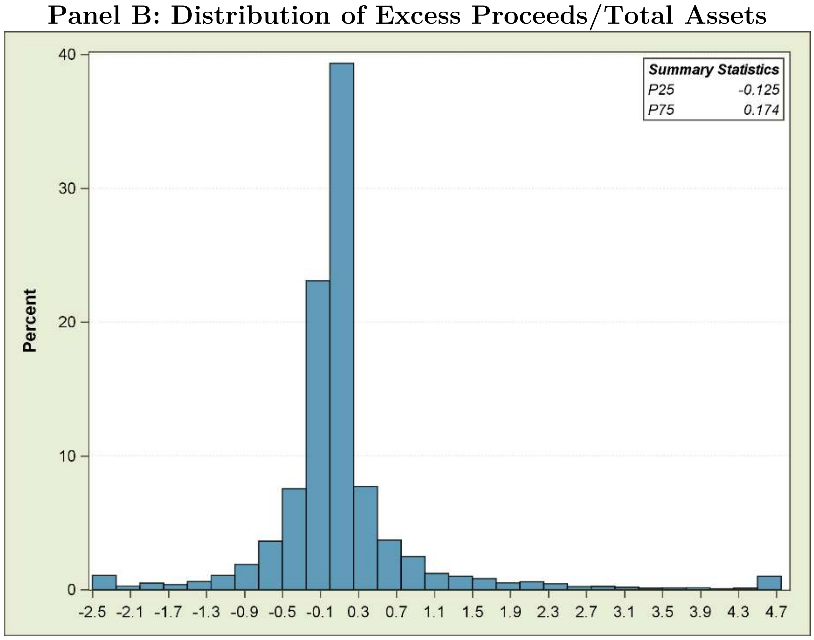


Figure 1.2: Distributions of Price Revisions and Share Revisions

This figure shows the distributions of price revisions and share revisions. The y-axis is the percentage of IPOs. The left, middle and right groups represent a decrease, no change, and an increase in price revisions, respectively. Within each group, the left, middle and right bars represent a decrease, no change, and an increase in share revisions. Price revisions are the percentage changes from the initial midpoint of the filing price range to offer prices. Share revisions are the percentage changes from primary shares filed to primary shares offered. Amended filing information is used if the initial filing information is missing.

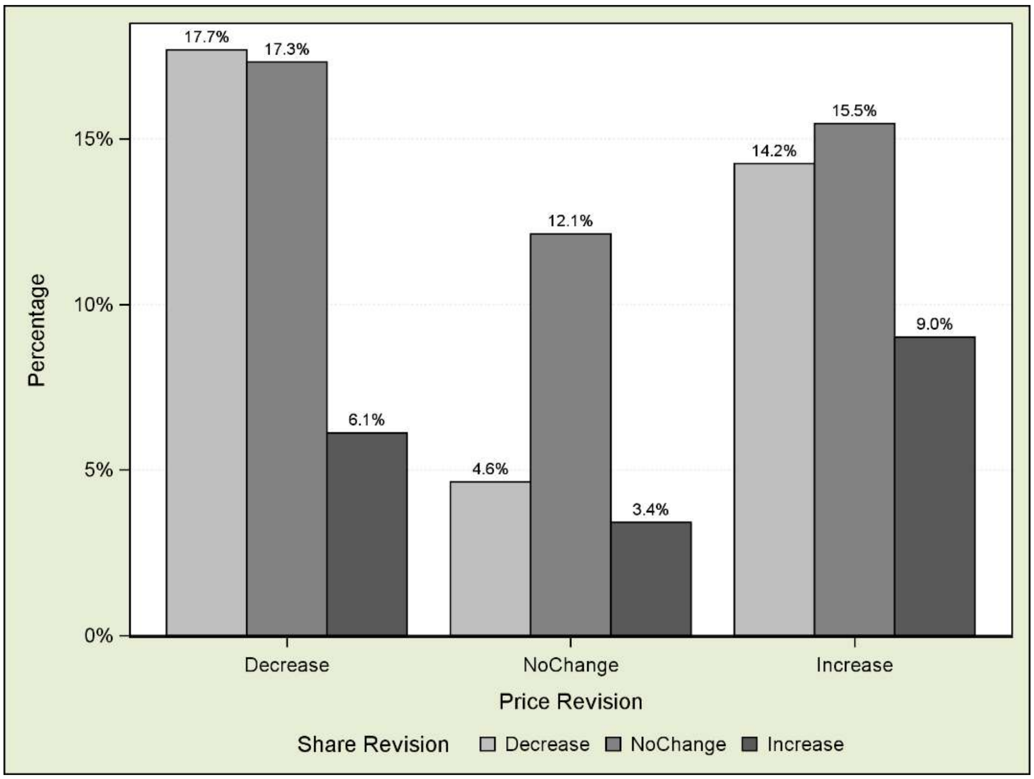


Figure 1.3: Stock Performance: High- vs. Low-Excess Proceeds Groups

This figure displays cumulative abnormal returns for high- versus low-excess proceeds portfolios in calendar time. The figure covers the period February 1984 and December 2018. Each year, IPOs are split into high and low groups based on the median of excess proceeds/filing proceeds (Panel A) and excess proceeds/total assets (Panel B) from year t-10 and t-1. Monthly abnormal returns are extracted from the residuals of calendar time portfolio regressions on purged Fama and French three factors and purged investment factor.

Panel A: By Excess Proceeds/Filing Proceeds

Panel B: By Excess Proceeds/Total Assets

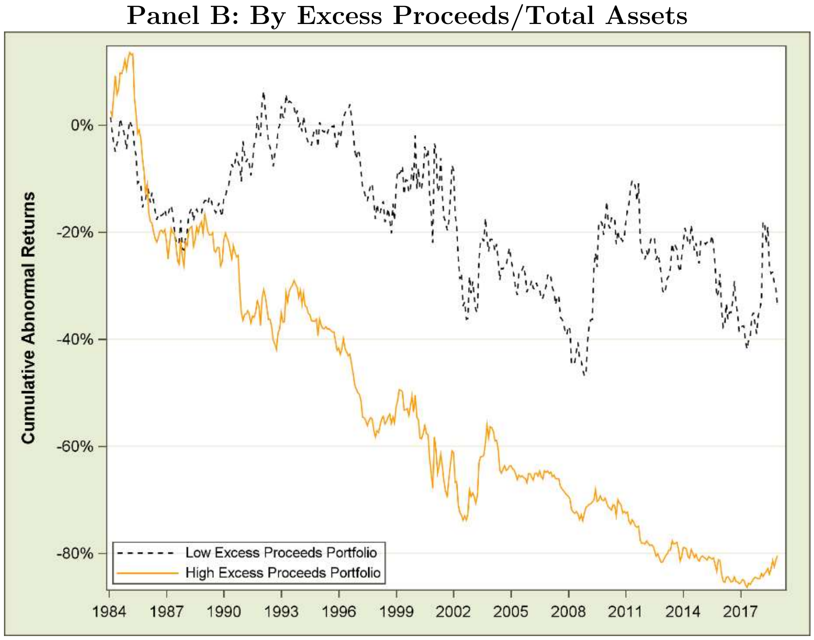


Table 1.1

Descriptive Statistics for the Initial Public Offering (IPO) Sample

This table reports the summary statistics for the IPO sample. The sample consists of 6,295 IPOs from 1983 to 2017. Unit offers, ADRs, REITs, closed-end funds, IPOs with offer prices below $1, IPOs from the financial and utility industry, pure secondary shares offerings and IPOs with share codes out of 10 and 11 are excluded from the sample. Additionally, IPOs with missing filing dates, with filing period (between filing dates and IPO dates) above 365, or with missing total assets or total assets below $1 million are excluded. Price Revisions are the percentage changes from the initial midpoint of filing price range to offer prices. If it is missing, I use the amended filing information. Primary Share Revisions are the percentage change from primary shares filed to primary shares offered. If the initial number of primary shares filed is missing, I replace it with the amended number of primary shares filed. Excess Proceeds are the difference between filing proceeds and the offered primary proceeds amount. Market Excess Proceeds and Idiosyncratic Excess Proceeds of Excess Proceeds/Total Assets are the predicted component and residual by regressing Excess Proceeds/Filing proceeds on the filing period value-weighted market returns and are rescaled by Total Assets. Overallotment amt/total assets are the amount from underwriters' exercise of the overallotment options. Filing-Period Market Returns are the cumulative value-weighted market returns, which begin on IPO filing dates and ends one day before IPO dates. Filing-Period Market Returns_Negative equals Filing-period market returns if it is negative, and 0 otherwise. Following Edelen and Kadlec (2005), Filing Amount/Total Equity value is the initial (or amended) filing amount (both primary and secondary) divided by the total market value of all CRSP firms one month before the filing month, divided by 1,000,000. Venture Capital Backed is a dummy variable that equals one if an IPO was backed by venture capitalists. Underwriter Rankings are the Carter and Manaster reputation measure. Spillover Revisions and Spillover Returns are the average price revisions and IPO underpricing completed from 30 days before the offerings, respectively. Overhang is defined as pre-IPO shares minus the number of secondary shares filed, divided by the total number of shares filed. If pre-IPO shares on SDC are missing, I complement them with Compustat pre-IPO shares. The Number of Book Runners is from SDC. Revenue is the most recent revenue before IPOs from Compustat, if it is missing, I replace it with the pre-IPO revenue on SDC, and if the pre-IPO revenue is missing, I replace it with post-IPO revenue on SDC. To determine IPO underpricing, following Lowry and Schwert (2002, 2004), I use the first closing price from CRSP if price data are available within 14 calendar days after IPO dates. If CRSP data missing, I obtain the closing price on the first day of trading from SDC. If that is still unavailable, the close on the second day or the end of the first week (both from SDC) is used. High-Tech Industry is a dummy variable equals one for IPOs in high-tech industries. All variables except Venture Capital Backed and High-Tech Industry are winsorized at 1% and 99% level.

Variable	N	Mean	Median	Std Dev	P25	P75
Excess proceeds/Filing Proceeds	6295	0.03	0.00	0.331	-0.16	0.18
Excess proceeds/Total Assets	6295	0.10	0.00	0.824	-0.13	0.17
Market Excess Proceeds	6292	0.06	0.01	0.214	0.00	0.06
Idiosyncratic Excess Proceeds	6292	0.03	-0.01	0.769	-0.16	0.12
Price Revisions(%)	6295	-1.10	0.00	16.405	-10.53	8.33
Primary Share Revisions(%)	6295	-6.21	0.00	21.397	-16.36	0.00
Filing-Period Market Returns(%)	6292	3.14	2.66	5.678	-0.21	5.97
Filing-Period Market Returns_Negative(%)	6292	-0.79	0.00	2.164	-0.21	0.00
Filing Amt/Total Equity Value	6292	0.01	0.01	0.009	0.00	0.01
Venture Capital Backed	6295	0.42	0.00	0.493	0.00	1.00
Underwriter Rankings	5751	7.30	8.00	2.148	7.00	9.00
Spillover Revisions	6295	0.00	0.00	0.078	-0.06	0.06
Spillover Returns	6295	0.21	0.14	0.236	0.08	0.22
Overhang	6212	3.37	2.25	5.105	1.34	3.59
Number of Book Runners	6295	1.24	1.00	0.809	1.00	1.00
Ln(revenue)	6154	3.32	3.31	1.833	2.06	4.49
IPO Underpricing(%)	6275	18.74	7.14	34.522	0.00	23.70
Overallotment Amt/Total Assets	6295	0.21	0.07	0.372	0.00	0.24
High-Tech Industry	6295	0.53	1.00	0.499	0.00	1.00

Table 1.2

Determinants of Price Revisions, Primary Share Revisions and Excess Proceeds

This table presents the determinants of Price Revisions, Primary Share revisions and Excess Proceeds/Filing Proceeds. Price revisions are the changes from the initial midpoint of filing price range to offer prices. Primary share revisions are the changes from initial filing primary shares to the offered primary shares. Xprcds/Filing Proceeds are excess proceeds scaled by the filing proceeds. All dependent variables are multiplied by 100 to ease interpretation. Filing-Period Market Returns_Neg equals filing-period returns if negative and zero otherwise. Ln(Filing Amt) is the initial (or amended) filing amount (both primary and secondary) divided by the total market value of all CRSP firms one month before the filing month, divided by 1,000,000. VC is a dummy variable that equals one if an IPO was backed by venture capitalists. Underwriter rankings are the Carter and Manaster reputation measure. Spillover Revisions and Spillover Returns are the average price revisions and IPO underpricing completed from 30 days before the offerings, respectively. Overhang measures the unsold portion of outstanding shares in the IPOs, which is pre-IPO shares minus the number of secondary shares filed, divided by total number of shares filed. The Number of Book Runners is from SDC. Revenue is the most recent revenue before IPOs from Compustat, if it is missing, I replace it with the pre-IPO revenue on SDC and if the pre-IPO revenue is missing, I replace it with post-IPO revenue on SDC. All variables except VC are winsorized by 1% and 99%, and standard errors are clustered by industry. For each coefficient, the p-value is reported in parentheses.

	Price Revisions		Primary Share Revisions		Xprcds/Filing Prcds	
	(1)	(2)	(3)	(4)	(5)	(6)
Filing-Period Market Returns	15.310	15.364	22.634	25.295	46.695	45.202
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Filing-Period Market Returns_Neg	48.260	51.694	5.091	1.833	53.140	61.435
	(0.00)	(0.00)	(0.70)	(0.90)	(0.04)	(0.02)
Ln(Filing Amt)	-1.689	-1.908	-3.552	-2.705	-7.112	-7.422
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VC	1.208	1.501	-0.342	-1.006	0.254	0.784
	(0.23)	(0.06)	(0.64)	(0.15)	(0.83)	(0.42)
Underwriter Ranking	1.011	1.019	-0.837	-0.703	1.152	1.266
	(0.01)	(0.03)	(0.02)	(0.04)	(0.00)	(0.02)
Spillover Revisions	38.451	38.161	13.326	14.434	52.083	53.084
	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
Spillover Returns	12.843	13.177	0.612	-0.074	25.961	25.818
	(0.00)	(0.00)	(0.74)	(0.97)	(0.00)	(0.00)
Overhang		0.136		0.120		0.289
		(0.04)		(0.03)		(0.01)
Number of Book Runners		0.287		1.532		7.392
		(0.67)		(0.00)		(0.00)
Ln(revenue)		0.162		-1.034		-0.523
		(0.65)		(0.00)		(0.20)
Observations	5,404	5,258	5,404	5,258	5,404	5,258
R-squared	0.285	0.292	0.314	0.325	0.307	0.323
Year-by-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by	Industry	Industry	Industry	Industry	Industry	Industry

Table 1.3

IPO Use of Proceeds

This table shows the use of 1) Filing Proceeds, 2) Market Excess Proceeds, and 3) Idiosyncratic Excess Proceeds over the 1-4 years after equity financing. The dependent variable is Y=ln[((Vt-V0)/total_asset0)+1] for V=cash, and Y=ln[((∑Vi)/total_asset0)+1] for V=R&D, capital expenditures, long-term debt reduction, acquisition, dividends, and repurchases. Filing proceeds are the product of the low filing price and the initial filing number of primary shares. Whenever the initial filing price or filing number of shares is unavailable, I use the amended filing information and require that the filing proceeds calculated from the amended filing forms be no larger than the initial filing primary share amount. Market and Idiosyncratic Excess Proceeds are the predicted values and residuals from the yearly regression of excess proceeds/filing proceeds on the filing-period market returns and are rescaled by total assets. All regressions include year*industry fixed effects, and standard errors are clustered by firm. *, **, *** denote p<0.1, p<0.05 and p<0.01, respectively.

$$Y_t = \beta_1 \ln\left[\left(\frac{FilingPrcds}{TotalAsset_0}\right)+1\right] + \beta_2 \ln\left[\left(\frac{MktXprcds}{TotalAsset_0}\right)+1\right] + \beta_3 \ln\left[\left(\frac{IdsynXprcds}{TotalAsset_0}\right)+1\right] + \beta_4 \ln\left[\left(\frac{OtherSources}{TotalAsset_0}\right)+1\right] + \beta_5 \ln[TotalAsset_0] + Year * Industry\ F.E. + \varepsilon$$

		FilingPrcds	MktXprcds	IdsynXprcds	Others	Total Asset		
Y	t	β1	β2	β3	β4	β5	N	R-square
△ CASH	1	0.927***	0.049	0.192***	0.236***	0.023***	5,534	82.4%
	2	0.770***	0.018	0.151***	0.313***	0.042***	5,225	69.2%
	3	0.610***	-0.043	0.131***	0.342***	0.030***	4,692	59.2%
	4	0.565***	-0.003	0.087***	0.323***	0.036***	4,140	51.1%
∑ CAPEX	1	0.110***	-0.016	0.026***	0.107***	-0.004	5,535	45.6%
	2	0.230***	-0.065	0.056***	0.194***	0.001	5,237	58.4%
	3	0.261***	-0.043	0.062***	0.242***	0.009	4,718	59.4%
	4	0.264***	-0.037	0.055***	0.284***	0.013**	4,167	59.9%
∑ R&D	1	0.246***	0.029	0.042***	0.077***	0.008***	5,535	61.8%
	2	0.455***	-0.041	0.074***	0.087***	0.022***	5,237	65.7%
	3	0.563***	-0.150**	0.090***	0.099***	0.025***	4,718	67.0%
	4	0.628***	-0.202***	0.075***	0.109***	0.024***	4,167	65.9%
∑ ACQUISITION	1	0.013	0.022	-0.005	0.085***	0.003	5,529	23.6%
	2	0.000	0.115**	0.006	0.170***	0.000	5,214	33.2%
	3	-0.029	0.118**	0.000	0.212***	0.004	4,692	36.5%
	4	-0.030	0.110*	0.012	0.247***	0.008	4,140	39.1%
∑ LT_DEBT-REDCUCTION	1	-0.015	0.105***	-0.015**	0.183***	0.013***	5,535	33.1%
	2	-0.062***	0.121***	-0.023**	0.226***	0.018***	5,237	40.4%
	3	-0.127***	0.112**	-0.027**	0.295***	0.019***	4,718	45.0%
	4	-0.155***	0.063	-0.030*	0.349***	0.024***	4,167	50.8%
∑ DIVIDEND	1	0.063***	-0.027	-0.002	0.017***	0.009***	5,535	19.5%
	2	0.066***	-0.013	-0.003	0.015***	0.011***	5,237	19.4%
	3	0.081***	-0.021	0.001	0.012***	0.013***	4,718	20.2%
	4	0.090***	-0.035	0.000	0.014***	0.014***	4,167	20.9%
∑ REPURCHASE	1	0.029***	-0.013	0.004	0.014***	0.007***	5,535	12.6%
	2	0.046***	-0.005	0.003	0.010***	0.009***	5,237	13.9%
	3	0.057***	0.000	-0.006	0.016***	0.010***	4,718	15.3%
	4	0.074***	-0.017	-0.004	0.023***	0.013***	4,167	17.4%

Table 1.4
IPO Use of Proceeds (Excluding Underwriters' Impact)

This table shows the use of 1) Filing Proceeds, 2) Market Excess Proceeds, and 3) Idiosyncratic Excess Proceeds over the 1-4 years after equity financing. The dependent variable is Y=ln[((Vt-V0)/total_asset0)+1] for V=cash, and Y=ln[((∑Vi)/total_asset0)+1] for V=R&D, capital expenditures, long-term debt reduction, acquisition, dividends, and repurchases. Underwriters' impact are mitigated by first sorting all IPOs into terciles based on underwriters' ranking and decomposing the excess proceeds by year and underwriters' terciles. Filing proceeds are the product of the low filing price and the initial filing number of primary shares. Whenever the initial filing price or filing number of shares is unavailable, I use the amended filing information and require that the filing proceeds calculated from the amended filing forms be no larger than the initial filing primary share amount. Market and Idiosyncratic Excess Proceeds are the predicted values and residuals from the yearly regression of excess proceeds/filing proceeds on the filing-period market returns and are rescaled by total assets. All regressions include year*industry fixed effects, and standard errors are clustered by firm. *, **, *** denote p<0.1, p<0.05 and p<0.01, respectively.

$$Y_t = \beta_1 \ln\left[\left(\frac{FilingPrcds}{TotalAsset_0}\right)+1\right] + \beta_2 \ln\left[\left(\frac{MktXprcds}{TotalAsset_0}\right)+1\right] + \beta_3 \ln\left[\left(\frac{IdsynXprcds}{TotalAsset_0}\right)+1\right] + \beta_4 \ln\left[\left(\frac{OtherSources}{TotalAsset_0}\right)+1\right] + \beta_5 \ln[TotalAsset_0] + Year * Industry\ F.E. + \varepsilon$$

Y	t	FilingPrcds β1	MktXprcds β2	IdsynXprcds β3	Others β4	Total Asset β5	N	R-square
△ CASH	1	0.929***	0.119***	0.179***	0.244***	0.024***	5,552	82.4%
	2	0.770***	0.094*	0.142***	0.318***	0.044***	5,242	69.5%
	3	0.602***	0.054	0.129***	0.343***	0.031***	4,701	59.1%
	4	0.547***	0.117	0.089***	0.322***	0.036***	4,148	51.0%
∑ CAPEX	1	0.110***	-0.019	0.027***	0.107***	-0.003	5,553	45.4%
	2	0.225***	-0.049	0.060***	0.193***	0.002	5,254	58.1%
	3	0.257***	-0.019	0.062***	0.243***	0.009	4,727	59.3%
	4	0.261***	-0.022	0.051***	0.284***	0.014**	4,175	59.8%
∑ R&D	1	0.248***	0.039	0.039***	0.078***	0.009***	5,553	62.0%
	2	0.459***	-0.006	0.066***	0.089***	0.024***	5,254	65.7%
	3	0.566***	-0.103*	0.082***	0.100***	0.027***	4,727	66.9%
	4	0.631***	-0.126*	0.064***	0.111***	0.027***	4,175	65.8%
∑ ACQUISITION	1	0.011	-0.001	0.001	0.081***	0.003	5,547	23.3%
	2	-0.001	0.104**	0.006	0.169***	-0.001	5,231	33.1%
	3	-0.031	0.127**	-0.003	0.213***	0.004	4,701	36.6%
	4	-0.034	0.107*	0.014	0.247***	0.008	4,148	39.1%
∑ LT_DEBT-REDCUCTION	1	-0.007	0.088***	-0.019**	0.181***	0.014***	5,553	32.5%
	2	-0.054***	0.109**	-0.030***	0.225***	0.018***	5,254	40.0%
	3	-0.123***	0.112**	-0.029**	0.295***	0.019***	4,727	44.9%
	4	-0.148***	0.027	-0.026*	0.349***	0.024***	4,175	50.6%
∑ DIVIDEND	1	0.060***	-0.024	0.002	0.016***	0.009***	5,553	19.0%
	2	0.062***	-0.015	0.002	0.014***	0.010***	5,254	18.7%
	3	0.076***	-0.032	0.007	0.012***	0.012***	4,727	19.6%
	4	0.085***	-0.055*	0.008	0.013***	0.014***	4,175	20.4%
∑ REPURCHASE	1	0.029***	-0.018	0.004	0.015***	0.007***	5,553	12.7%
	2	0.046***	-0.006	0.003	0.010***	0.009***	5,254	13.9%
	3	0.056***	0.005	-0.007	0.016***	0.010***	4,727	15.2%
	4	0.070***	-0.011	-0.003	0.022***	0.013***	4,175	17.1%

Table 1.5

IPO Use of Proceeds (Hot Market IPOs, Price-Lowballing Incentives, and Life Cycle Story)

This table shows the use of 1) Filing Proceeds, 2) Market Excess Proceeds, and 3) Idiosyncratic Excess Proceeds over the 1-4 years after equity financing. The dependent variable is Y=ln[((Vt-V0)/total_asset0)+1] for V=cash, and Y=ln[((∑Vi)/total_asset0)+1] for V=R&D, capital expenditures, long-term debt reduction, acquisition, dividends, and repurchases. Filing proceeds are the product of the low filing price and the initial filing number of primary shares. Whenever the initial filing price or filing number of shares is unavailable, I use the amended filing information. Market and Idiosyncratic Excess Proceeds are the predicted values and residuals from the yearly regression of excess proceeds/filing proceeds on the filing-period market returns and are rescaled by total assets. HotMkt is a dummy variable for hot market IPOs. Htech is a dummy variable from Thomson Reuters SDC for High-Technology IPOs. Age is the founding age when a firm went public. Coefficients of Other sources and total assets are omitted due to space constraints. All regressions include year*industry fixed effects, and standard errors are clustered by firm. *, **, *** denote p<0.1, p<0.05 and p<0.01, respectively.

$$Y_t = \beta_1 \ln\left[\left(\frac{\text{FilingPrcds}}{\text{TotalAsset}_0}\right)+1\right] + \beta_2 \ln\left[\left(\frac{\text{MktXprcds}}{\text{TotalAsset}_0}\right)+1\right] + \beta_3 \ln\left[\left(\frac{\text{IdsynXprcds}}{\text{TotalAsset}_0}\right)+1\right] + \beta_4 \ln\left[\left(\frac{\text{OtherSources}}{\text{TotalAsset}_0}\right)+1\right]$$
$$+ \beta_5 \ln[\text{TotalAsset}_0] + \beta_6 \text{HotMkt} + \beta_7 \text{Htech} + \beta_8 \ln[\text{Age}+1] + \text{Year} * \text{Industry F.E.} + \varepsilon$$

Y	t	FilingPrcds β1	MktXprcds β2	IdsynXprcds β3	HotMkt β6	Htech β7	Age β8	N	R-Square
△ CASH	1	0.901***	0.057	0.193***	0.016	0.137***	0.006	5,396	83.3%
	2	0.738***	0.034	0.151***	0.012	0.199***	0.01	5,103	70.5%
	3	0.577***	-0.026	0.130***	0.000	0.238***	0.006	4,582	60.5%
	4	0.532***	-0.001	0.086***	0.011	0.290***	0.013	4,045	52.5%
∑ CAPEX	1	0.112***	-0.018	0.025***	-0.012*	-0.019**	-0.018***	5,397	46.5%
	2	0.233***	-0.061	0.054***	0.000	-0.023*	-0.025***	5,115	58.6%
	3	0.258***	-0.035	0.059***	-0.007	-0.002	-0.032***	4,607	59.6%
	4	0.255***	-0.024	0.051***	-0.009	0.012	-0.035***	4,071	60.2%
∑ R&D	1	0.233***	0.032	0.042***	0.000	0.103***	-0.004	5,397	63.7%
	2	0.427***	-0.037	0.074***	-0.003	0.213***	-0.012**	5,115	68.2%
	3	0.521***	-0.150**	0.087***	-0.014	0.321***	-0.021***	4,607	70.2%
	4	0.570***	-0.211***	0.072***	-0.013	0.418***	-0.024***	4,071	69.8%
∑ ACQUISITION	1	0.02	0.026	-0.005	-0.018**	-0.037***	0.001	5,392	24.3%
	2	0.012	0.120**	0.008	-0.02	-0.071***	0.016**	5,093	34.3%
	3	-0.015	0.123**	0.002	-0.019	-0.078***	0.023***	4,582	37.5%
	4	-0.016	0.114*	0.014	-0.026	-0.101***	0.024**	4,045	40.1%
∑ LT_DEBT-REDCUCTION	1	-0.007	0.106***	-0.014*	0.014	-0.076***	0.025***	5,397	35.3%
	2	-0.049**	0.121***	-0.020*	0.013	-0.115***	0.026***	5,115	42.3%
	3	-0.107***	0.112**	-0.022*	0.005	-0.162***	0.038***	4,607	47.2%
	4	-0.135***	0.052	-0.024	-0.009	-0.180***	0.048***	4,071	52.9%
∑ DIVIDEND	1	0.066***	-0.029	-0.001	-0.001	-0.014***	0.012***	5,397	20.2%
	2	0.070***	-0.015	-0.003	-0.001	-0.021***	0.010***	5,115	20.3%
	3	0.086***	-0.023	0.003	-0.005	-0.026***	0.009***	4,607	21.4%
	4	0.097***	-0.037	0.002	-0.012	-0.032***	0.007**	4,071	22.0%
∑ REPURCHASE	1	0.029***	-0.011	0.003	0.005	0.006	0.002	5,397	13.1%
	2	0.047***	-0.001	0.003	0.004	0.003	0.002	5,115	14.2%
	3	0.058***	0.003	-0.007	0.000	0.004	0.003	4,607	15.5%
	4	0.076***	-0.014	-0.005	-0.008	0.010	0.000	4,071	17.7%

Table 1.6
IPO Use of Proceeds (With Overallotment Option Amount)

This table shows the use of 1) Filing proceeds, 2) Market Excess Proceeds, and 3) Idiosyncratic Excess Proceeds over the 1-4 years after equity financing. The dependent variable is Y=ln[((Vt-V0)/total_asset0)+1] for V=cash, and Y=ln[((∑Vi)/total_asset0)+1] for V=R&D, capital expenditures, long-term debt reduction, acquisition, dividends, and repurchases. Filing proceeds are the product of the low filing price and the initial filing number of primary shares. Whenever the initial filing price or filing number of shares is unavailable, I use the amended filing information and require that the filing proceeds calculated from the amended filing forms be no larger than the initial filing primary share amount. Market and Idiosyncratic Excess Proceeds are the predicted values and residuals from the yearly regression of excess proceeds/filing proceeds on the filing-period market returns and are rescaled by total assets. OvAMT is the overallotment option amount. All regressions include year*industry fixed effects, and standard errors are clustered by firm. *, **, *** denote p<0.1, p<0.05 and p<0.01, respectively.

$$Y_t = \beta_1 \ln\left[\left(\frac{FilingPrcds}{TotalAsset_0}\right)+1\right] + \beta_2 \ln\left[\left(\frac{MktXprcds}{TotalAsset_0}\right)+1\right] + \beta_3 \ln\left[\left(\frac{IdsynXprcds}{TotalAsset_0}\right)+1\right] + \beta_4 \ln\left[\left(\frac{OtherSources}{TotalAsset_0}\right)+1\right]$$
$$+ \beta_5 \ln[TotalAsset_0] + \beta_6 \ln\left[\left(\frac{Overallotment\ Amt}{TotalAsset_0}\right)+1\right] + Year * Industry\ F.E. + \varepsilon$$

Y	t	FilingPrcds β1	MktXprcds β2	IdsynXprcds β3	Others β4	Total Asset β5	OvAMT β6	N	R-square
△ CASH	1	0.826***	0.005	0.161***	0.214***	0.016***	0.360***	5,534	82.9%
	2	0.636***	-0.033	0.110***	0.296***	0.033***	0.484***	5,225	70.1%
	3	0.478***	-0.097	0.091***	0.332***	0.020**	0.466***	4,692	60.0%
	4	0.430***	-0.051	0.050**	0.315***	0.026***	0.469***	4,140	51.8%
∑ CAPEX	1	0.115***	-0.013	0.028***	0.108***	-0.003	-0.019	5,535	45.6%
	2	0.209***	-0.073*	0.050***	0.191***	0.000	0.073*	5,237	58.5%
	3	0.220***	-0.060	0.049***	0.239***	0.006	0.146***	4,718	59.6%
	4	0.197***	-0.061	0.036***	0.280***	0.008	0.234***	4,167	60.3%
∑ R&D	1	0.229***	0.021	0.037***	0.073***	0.007***	0.059**	5,535	61.9%
	2	0.437***	-0.048	0.069***	0.085***	0.021***	0.066	5,237	65.7%
	3	0.517***	-0.169***	0.076***	0.095***	0.022***	0.163***	4,718	67.1%
	4	0.560***	-0.227***	0.056***	0.105***	0.019**	0.236***	4,167	66.1%
∑ ACQUISITION	1	0.020	0.025	-0.002	0.087***	0.004	-0.027	5,529	23.6%
	2	0.007	0.118**	0.009	0.171***	0.001	-0.028	5,214	33.2%
	3	-0.035	0.115**	-0.002	0.212***	0.004	0.023	4,692	36.5%
	4	-0.043	0.106	0.008	0.246***	0.007	0.044	4,140	39.1%
∑ LT_DEBT-REDCUCTION	1	0.048***	0.132***	0.004	0.196***	0.017***	-0.222***	5,535	34.3%
	2	0.010	0.149***	-0.001	0.235***	0.023***	-0.259***	5,237	41.3%
	3	-0.046	0.146***	-0.002	0.302***	0.025***	-0.288***	4,718	45.8%
	4	-0.065*	0.096	-0.004	0.355***	0.030***	-0.314***	4,167	51.4%
∑ DIVIDEND	1	0.067***	-0.025	0.000	0.018***	0.010***	-0.016	5,535	19.5%
	2	0.064***	-0.014	-0.003	0.014***	0.010***	0.008	5,237	19.4%
	3	0.081***	-0.021	0.001	0.012***	0.013***	0.000	4,718	20.2%
	4	0.082***	-0.038	-0.002	0.013***	0.014***	0.028	4,167	21.0%
∑ REPURCHASE	1	0.034***	-0.011	0.005	0.015***	0.007***	-0.018	5,535	12.7%
	2	0.042***	-0.006	0.002	0.010***	0.009***	0.015	5,237	13.9%
	3	0.042***	-0.006	-0.010	0.015***	0.009***	0.050**	4,718	15.5%
	4	0.051***	-0.026	-0.011	0.021***	0.011***	0.083***	4,167	17.8%

Table 1.7

3-Year IPO Long-Run Stock Performance

This table reports 3-year IPO long-run stock underperformance in the calendar-time portfolio approach. The base model is Rpt - Rft = a + bt (Rmt - Rft) + stPurgedSMBt + htPurgedHMLt +vtPurgedINVTt, where Rpt = the monthly return on an equally weighted calendar-time portfolio; Rft = the monthly on the 3-month T-bill; a is the intercept, the mean monthly abnormal return on the calendar-time portfolio; Rmt is the monthly return of the value-weighted market index. Following Loughran and Ritter (2000), I create purged SMB, HML and Investment factors by excluding firms that had IPOs or SEOs in the past five years, which are denoted as PurgedSMB, PurgedHML and PurgedINVT. I further restrict that each portfolio have at least 10 observations to estimate the regression parameters, and the portfolio a is reported by weighing the number of IPOs in each month. Each year, IPOs are split into high and low groups based on the medians of Excess Proceeds/Total Assets, Excess Proceeds/Filing Proceeds, Price Revisions, and IPO First-day Underpricing from year t-10 to t-1. Panels A, B, C, and D summarize the a and *p*-value, respectively. To compare the a between High and Low groups, I also create a portfolio that long High groups' IPOs and short Low groups' IPOs, which are denoted as High-Low. Panel E and F further split the high Excess Proceeds/Total Assets and Excess Proceeds/Filing Proceeds into two groups by the portion of Market Excess Proceeds (Market Excess Proceeds/Idiosyncratic Excess Proceeds). For each a, the *p-value* is reported in parentheses.

	High	**Low**	**High-Low**	**N**
Panel A: By Excess Proceeds/Total Assets				
Model 1: Purged FF3F	-0.488	-0.187	-0.306	419
	(0.02)	(0.30)	(0.02)	
Model 2: Purged FF3F & Purged INVT	-0.438	-0.080	-0.339	419
	(0.05)	(0.66)	(0.01)	
Panel B: By Excess Proceeds/Filing Proceeds				
Model 1: Purged FF3F	-0.502	-0.179	-0.338	419
	(0.01)	(0.35)	(0.00)	
Model 2: Purged FF3F & Purged INVT	-0.447	-0.079	-0.364	419
	(0.03)	(0.68)	(0.00)	
Panel C: By Price Revisions				
Model 1: Purged FF3F	-0.294	-0.343	0.057	408
	(0.17)	(0.07)	(0.67)	
Model 2: Purged FF3F & Purged INVT	-0.252	-0.235	0.019	408
	(0.25)	(0.21)	(0.89)	
Panel D: By IPO First-day Underpricing				
Model 1: Purged FF3F	-0.369	-0.296	-0.039	418
	(0.09)	(0.10)	(0.76)	
Model 2: Purged FF3F & Purged INVT	-0.323	-0.188	-0.104	418
	(0.14)	(0.29)	(0.42)	

Table 1.7 continues on the next page

Table 1.7 continues from the previous page

	High	**Low**	**High-Low**	**N**
Panel E: Splitting High Excess Proceeds/Total Assets by the Portion of Market Excess Proceeds				
Model 1: Purged FF3F	-0.485	-0.476	0.033	390
	(0.02)	(0.07)	(0.83)	
Model 2: Purged FF3F & Purged INVT	-0.422	-0.446	0.047	390
	(0.05)	(0.09)	(0.77)	
Panel F: Splitting High Excess Proceeds/Filing Proceeds by the Portion of Market Excess Proceeds				
Model 1: Purged FF3F	-0.466	-0.561	0.114	390
	(0.03)	(0.02)	(0.48)	
Model 2: Purged FF3F & Purged INVT	-0.398	-0.525	0.134	390
	(0.06)	(0.03)	(0.42)	

Table 1.8
Excess Proceeds and the 3-Year IPO Delisting Probability

This table examines the relation between excess proceeds and the 3-year IPO delisting probability. Delisting is a dummy variable equals one if a firm delists within three years after IPO and has delisting codes between 300 and 599 on CRSP (Exchanges, Liquidations, and Dropped). Acquired is a dummy variable that equals one if a firm is acquired within three years after IPO and has delisting codes between 200 and 299 (Mergers). Column (1) to (4) report the delisting probability using the Probit model and Column (5) to (8) using the Linear Probability model. The coefficients have been converted to marginal effects in probit models. All control variables are extracted from Compustat annual database, and all coefficients are multiplied by 100 to ease interpretation. Each year, IPOs are split into high and low excess proceeds groups based on the medians of Xprcds/Total Assets and Xprcds/Filing Proceeds from year t-10 to t-1. High Xprcds/Total Assets and High Xprcds/Filing Prcds are dummy variables equal one for the high excess proceed group. Tangibility is equal to property, plant, and equipment, scaled by total assets. Rating is a dummy variable that equals one if a firm has any of the following credit ratings: domestic long-term issuer credit rating, subordinated debt rating, and short-term issuer credit rating. Log(Filing Amount) is the log values of initial (or amended) filing amount (both primary and secondary) divided by the total market value of all CRSP firms one month before the filing month, divided by 1,000,000. VC is a dummy variable for venture-capital-backed IPOs. Underwriter Ranking is the Carter and Manaster reputation measure. All variables except VC are winsorized by 1% and 99%, and standard errors are clustered by industry. For each coefficient, the *p-value* is reported in parentheses.

	Probit Model				Linear Probability Model			
Variables	Delisting		Acquired		Delisting		Acquired	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Xprcds/Total Assets	1.251		-0.461		1.627		-0.474	
	(0.03)		(0.55)		(0.03)		(0.63)	
High Xprcds/Filing Prcds		1.026		-0.728		1.482		-0.758
		(0.03)		(0.34)		(0.02)		(0.44)
Cash	-4.381	-4.290	-1.146	-1.098	-6.354	-6.271	-0.546	-0.484
	(0.00)	(0.00)	(0.56)	(0.57)	(0.01)	(0.01)	(0.80)	(0.82)
Ln(Total Assets)	-4.272	-4.199	0.106	0.150	-5.588	-5.505	0.124	0.172
	(0.00)	(0.00)	(0.92)	(0.89)	(0.00)	(0.00)	(0.93)	(0.90)
Leverage	9.959	10.015	3.802	3.712	15.254	15.365	4.361	4.253
	(0.00)	(0.00)	(0.18)	(0.20)	(0.00)	(0.00)	(0.26)	(0.27)
Tobin's Q	-0.386	-0.384	-0.559	-0.554	-0.471	-0.468	-0.725	-0.721
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tangibility	-1.143	-1.129	-6.229	-6.291	1.167	1.225	-6.289	-6.327
	(0.26)	(0.27)	(0.00)	(0.00)	(0.52)	(0.50)	(0.00)	(0.00)
Rating	0.570	0.478	0.210	0.241	1.735	1.605	1.679	1.717
	(0.73)	(0.77)	(0.91)	(0.89)	(0.47)	(0.50)	(0.50)	(0.48)
Log(Filing Amount)	1.586	1.491	-0.378	-0.430	2.050	1.962	-0.036	-0.095
	(0.04)	(0.04)	(0.70)	(0.66)	(0.03)	(0.02)	(0.98)	(0.93)
VC	0.720	0.695	-0.024	-0.035	0.634	0.624	-0.737	-0.753
	(0.34)	(0.35)	(0.98)	(0.98)	(0.60)	(0.61)	(0.61)	(0.60)
Underwriter Ranking	-0.837	-0.838	1.638	1.631	-1.788	-1.787	1.282	1.273
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Observations	5,225	5,225	5,351	5,351	5,130	5,130	5,130	5,130
R2	21.1%	21.0%	6.7%	6.7%	11.5%	11.5%	1.9%	1.9%
Year FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Year*Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Cluster by	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry

Table 1.9

Excess Proceeds and the 3-Year IPO Delisting Speed

This table examines the relation between excess proceeds and the 3-year IPO delisting speed in the hazard model. Delisting is a dummy variable that equals one if a firm delists within three years after IPO and has delisting codes between 300 and 599 on CRSP (Exchanges, Liquidations, and Dropped). Acquired is a dummy variable equals one if a firm is acquired within three years after IPO and has delisting codes between 200 and 299 (Mergers). All control variables are extracted from Compustat quarterly database, and all coefficients have been converted into hazard ratios. Each year, IPOs are split into high and low excess proceeds groups based on the medians of Xprcds/Total Assets and Xprcds/Filing Proceeds from year t-10 to t-1. High Xprcds/Total Assets and High Xprcds/Filing Prcds are dummy variables that equal one for the high excess proceed group. Tangibility is equal to property, plant, and equipment, scaled by total assets. Rating is a dummy variable that equals one if a firm has any of the following credit ratings: a domestic long-term issuer credit rating, a subordinated debt rating, and a short-term issuer credit rating. Log(Filing Amount) is the log value of initial (or amended) filing amount (both primary and secondary) divided by the total market value of all CRSP firms one month before the filing month, divided by 1,000,000. VC is a dummy variable for venture-capital-backed IPOs. Underwriter Ranking is the Carter and Manaster reputation measure. All variables except VC are winsorized by 1% and 99%, and standard errors are clustered by industry. For each coefficient, the *p-value* is reported in parentheses. All coefficients have been converted to Hazard ratios.

	Hazard Model			
Variables	Delisting		Acquired	
	(1)	(2)	(3)	(4)
High Xprcds/Total Assets	1.556		1.031	
	(0.00)		(0.68)	
High Xprcds/Filing Prcds		1.481		0.948
		(0.01)		(0.53)
Cash	0.145	0.147	0.339	0.344
	(0.00)	(0.00)	(0.00)	(0.00)
Ln(Total Assets)	0.301	0.303	0.838	0.845
	(0.00)	(0.00)	(0.00)	(0.00)
Leverage	20.845	21.004	1.152	1.132
	(0.00)	(0.00)	(0.54)	(0.59)
Tobin's Q	0.870	0.869	1.034	1.035
	(0.02)	(0.02)	(0.08)	(0.08)
Tangibility	1.106	1.121	0.554	0.555
	(0.68)	(0.64)	(0.02)	(0.02)
Rating	1.867	1.838	1.211	1.213
	(0.02)	(0.03)	(0.45)	(0.45)
Log(Filing Amount)	1.493	1.480	1.106	1.095
	(0.02)	(0.02)	(0.27)	(0.32)
VC	1.074	1.069	1.076	1.070
	(0.70)	(0.72)	(0.53)	(0.56)
Underwriter Ranking	0.972	0.971	1.180	1.179
	(0.57)	(0.57)	(0.00)	(0.00)
Observations	37,857	37,857	37,857	37,857
R2	19.5%	19.4%	3.9%	3.9%
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster by	Industry	Industry	Industry	Industry

Table 1.10

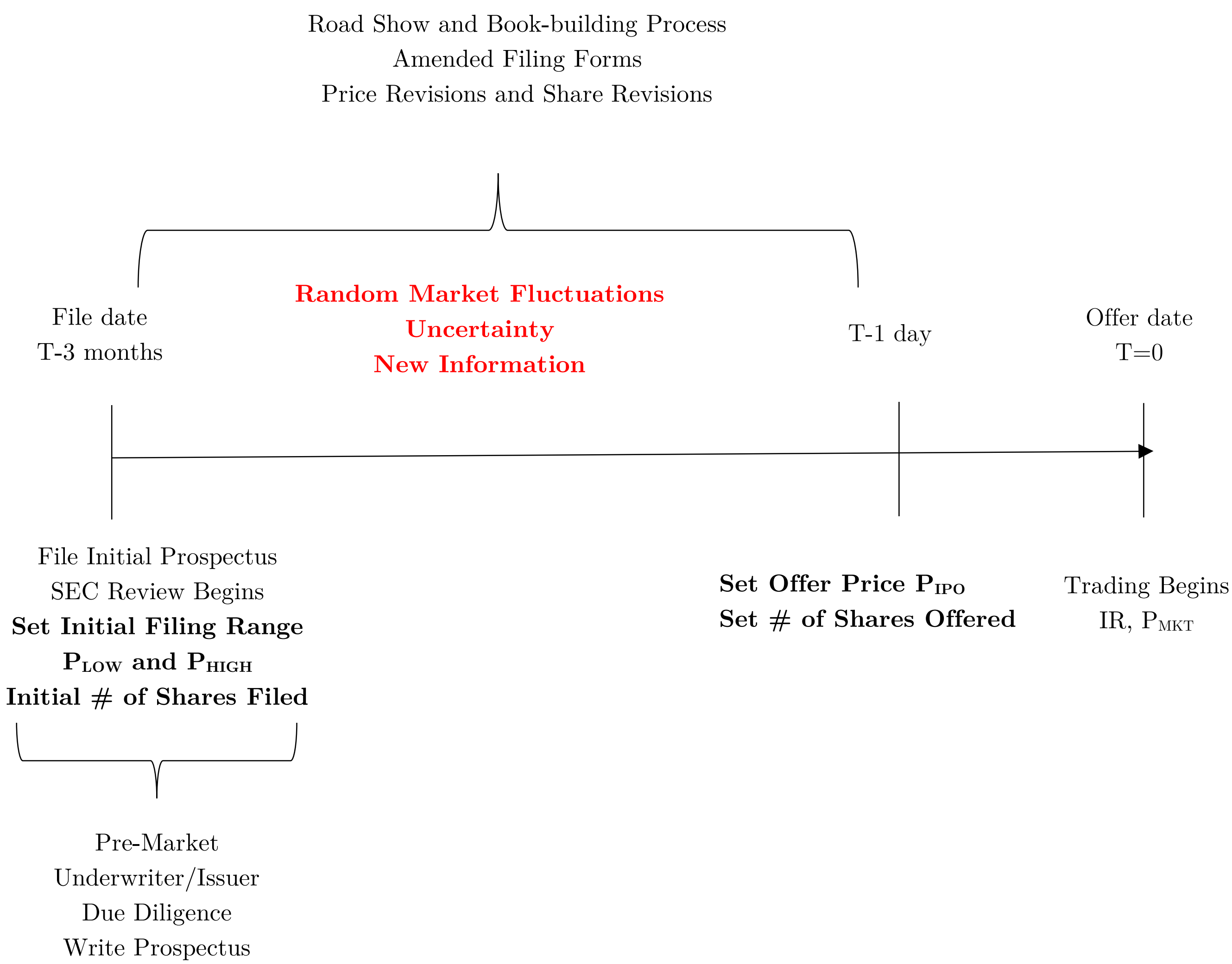
Excess Proceeds and 3-Year Future Financings

This table examines the relation between excess proceeds and the speed of returning to the stock market within three years after IPOs using the hazard model. Following McKeon (2015) and Huang and Ritter (2018), Equity Issue and Debt Issue equal one if a firm's net equity amount or net debt amount in a quarter is larger than 5% of the book value of assets and at least 3% of the market value of equity. All Issue equals one if a firm issued either equity or debt in a quarter. All control variables are extracted from Compustat quarterly database, and all coefficients have been converted into hazard ratios. Each year, IPOs are split into high and low excess proceeds groups based on Xprcds/Total Assets and Xprcds/Filing proceeds. High Xprcds/Total Assets and High Xprcds/Filing Prcds are dummy variables that equal one for the high excess proceed group. Tangibility is equal to property, plant, and equipment, scaled by total assets. Rating is a dummy variable that equals one if a firm has any of the following credit ratings: domestic long-term issuer credit rating, subordinated debt rating, and short-term issuer credit rating. Log(Filing Amount) is the log values of initial (or amended) filing amount (both primary and secondary) divided by the total market value of all CRSP firms one month before the filing month, divided by 1,000,000. VC is a dummy variable for venture-capital-backed IPOs. Underwriter Ranking is the Carter and Manaster reputation measure. All variables except VC are winsorized by 1% and 99%, and standard errors are clustered by industry. For each coefficient, the p-value is reported in parentheses.

	Hazard Ratio					
Variables	Equity Issue		Debt Issue		All Issue	
	(1)	(2)	(3)	(4)	(5)	(6)
High Xprcds/Total Assets	0.837		0.933		0.904	
	(0.00)		(0.02)		(0.00)	
High Xprcds/Filing Prcds		0.825		0.975		0.915
		(0.00)		(0.47)		(0.03)
Cash	4.379	4.361	0.160	0.159	1.043	1.037
	(0.00)	(0.00)	(0.00)	(0.00)	(0.83)	(0.85)
Ln(Total Assets)	1.357	1.358	1.109	1.103	1.204	1.200
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Leverage	0.609	0.604	9.906	9.937	4.619	4.612
	(0.10)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)
Tobin's Q	1.030	1.030	0.899	0.899	0.988	0.988
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.07)
Tangibility	0.986	0.974	0.763	0.760	0.804	0.798
	(0.92)	(0.86)	(0.01)	(0.01)	(0.02)	(0.02)
Rating	1.079	1.085	0.705	0.705	0.732	0.734
	(0.57)	(0.54)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Filing Amount)	0.705	0.704	0.828	0.834	0.784	0.787
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VC	1.051	1.052	1.178	1.180	1.103	1.105
	(0.35)	(0.35)	(0.00)	(0.00)	(0.09)	(0.08)
Underwriter Ranking	0.879	0.879	0.981	0.982	0.942	0.943
	(0.00)	(0.00)	(0.18)	(0.21)	(0.00)	(0.00)
Observations	38,088	38,088	38,088	38,088	38,088	38,088
R2	2.6%	2.6%	5.4%	5.4%	1.9%	1.9%
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by	Industry	Industry	Industry	Industry	Industry	Industry

Appendix 1.A1: Offering Process (Following Figure 2 in Hanley 2017)

This figure presents a timeline for the offering process. P_{HIGH} and P_{LOW} are the high and low boundary of the initial filing price range in the preliminary prospectus. Initial # of Shares Filed and # of Shares Offered are the filing and offering number of primary shares. P_{IPO} is the final offer price. IR is the first-day underpricing, which is measured as the percentage change from P_{IPO} to the first-day closing price P_{MKT}.



Appendix 1.A2: Backfill SDC Variables

Thomson Reuters SDC platinum occasionally provides incomplete information for specific variables, but we could infer the information from the other variables. For example, the secondary share offered variable is set to a missing value when the offer is a pure primary share offering. In this case, backfilling SDC variables is necessary.

First, 1,503 IPOs (*before dropping missing values in excess proceeds*) have non-missing values in "*proceeds amount filed*" but missing values in "*primary proceeds amount filed*" and the "*type filed*" indicates that the filings are pure primary shares. In this case, I replace the "*primary proceeds amount filed*" with "*proceeds amount filed*". Furthermore, based on the variable definition of the "*number of primary shares filed*" on SDC, for missing values of "*number of primary shares filed*", I compute the number of primary shares as $\frac{\text{Primary } \ Amount\ Filed * 1{,}000{,}000}{Middle\ Filing\ price}$. Second, some issuers did not provide complete information, such as the "*filing price range*" and "*the number of primary shares filed*", on the initial filing dates. Instead, these issuers submitted amended forms to the SEC after the initial filing dates, and this information, for example, the "*amended the number of primary shares filed*" variable is also available on SDC. Whenever the initial filing information is unavailable, I use the amended filing information provided by the SDC database.

Table 1.A3

IPO Use of Proceeds (Use Linear Scale)

This table shows the use of 1) Filing proceeds, 2) Market Excess Proceeds, and 3) Idiosyncratic Excess Proceeds over the 1-4 years after equity financing. The dependent variable is Y=ln[((Vt-V0)/total_asset0)+1] for V=cash, and Y=ln[((∑Vi)/total_asset0)+1] for V=R&D, capital expenditures, long-term debt reduction, acquisition, dividends, and repurchases. Filing proceeds are the product of the low filing price and the initial filing number of primary shares. Whenever the initial filing price or filing number of shares is unavailable, I use the amended filing information and require that the filing proceeds calculated from the amended filing forms be no larger than the initial filing primary share amount. Market and Idiosyncratic Excess Proceeds are the predicted values and residuals from the yearly regression of excess proceeds/filing proceeds on the filing-period market returns and are rescaled by total assets. All regressions include year*industry fixed effects, and standard errors are clustered by firm. *, **, *** denote p<0.1, p<0.05 and p<0.01, respectively.

$$Y_t = \beta_1 \ln\left[\left(\frac{FilingPrcds}{TotalAsset_0}\right)+1\right] + \beta_2 \frac{MktXprcds}{TotalAsset_0} + \beta_3 \frac{IdsynXprcds}{TotalAsset_0} + \beta_4 \ln\left[\left(\frac{OtherSources}{TotalAsset_0}\right)+1\right] + \beta_5 \ln[TotalAsset_0] + Year * Industry\ F.E. + \varepsilon$$

Y	t	FilingPrcds β1	MktXprcds β2	IdsynXprcds β3	Others β4	Total Asset β5	N	R-square
△ CASH	1	0.854***	0.043	0.166***	0.237***	0.014***	5,816	82.1%
	2	0.697***	0.010	0.146***	0.316***	0.034***	5,498	69.4%
	3	0.583***	-0.087	0.112***	0.345***	0.029***	4,924	59.6%
	4	0.538***	-0.100	0.088***	0.328***	0.036***	4,358	51.6%
∑ CAPEX	1	0.108***	0.004	0.017***	0.113***	-0.004	5,817	46.6%
	2	0.217***	-0.048	0.050***	0.196***	0.001	5,510	58.9%
	3	0.247***	-0.047	0.055***	0.244***	0.009	4,951	59.7%
	4	0.248***	-0.060	0.052***	0.285***	0.013**	4,386	60.1%
∑ R&D	1	0.232***	0.004	0.037***	0.076***	0.007***	5,817	61.8%
	2	0.428***	-0.040	0.065***	0.089***	0.019***	5,510	65.6%
	3	0.533***	-0.125**	0.073***	0.104***	0.022***	4,951	67.0%
	4	0.604***	-0.190***	0.066***	0.113***	0.023***	4,386	66.2%
∑ ACQUISITION	1	0.018	0.040	-0.004	0.077***	0.005	5,811	22.5%
	2	-0.002	0.116***	0.007	0.165***	0.000	5,486	33.6%
	3	-0.016	0.119**	-0.003	0.206***	0.007	4,925	36.2%
	4	-0.026	0.116**	0.011	0.241***	0.010	4,359	38.4%
∑ LT_DEBT-REDCUCTION	1	-0.012	0.070***	-0.006	0.172***	0.015***	5,817	32.2%
	2	-0.053***	0.103***	-0.019**	0.224***	0.019***	5,510	40.6%
	3	-0.106***	0.078*	-0.033***	0.293***	0.022***	4,951	44.7%
	4	-0.148***	0.057	-0.021*	0.343***	0.025***	4,386	49.8%
∑ DIVIDEND	1	0.062***	-0.023	-0.001	0.018***	0.009***	5,817	19.8%
	2	0.068***	-0.025	-0.002	0.013***	0.010***	5,510	19.6%
	3	0.078***	-0.040*	0.002	0.013***	0.012***	4,951	20.1%
	4	0.089***	-0.043*	-0.002	0.014***	0.013***	4,386	20.9%
∑ REPURCHASE	1	0.032***	-0.012	0.002	0.015***	0.007***	5,817	12.1%
	2	0.045***	-0.005	0.002	0.011***	0.009***	5,510	13.2%
	3	0.056***	0.004	-0.001	0.016***	0.010***	4,951	14.9%
	4	0.071***	-0.015	0.003	0.023***	0.013***	4,386	16.9%

Chapter 2 : Peer Issuance Activities and IPO Underperformance

Abstract

This paper analyzes the impact of subsequent industry-follower IPOs on newly public incumbents' long-term stock performance. Using a sample of 8,863 IPOs from 1983 through 2015, we document that long-run underperformance is reduced by approximately 60% after excluding returns on days around industry-follower IPO filings. Additionally, we show that newly public incumbents with small initial sizes, more growth opportunities, and experience high post-IPO sales growth are more sensitive to industry-follower IPO filing effects. These results highlight the impact of industry peers' financing activities on newly public incumbents' long-term stock performance.

Keywords: Initial public offerings, New issue puzzle, Peer effects

JEL Classifications: G14, G19, G32

2.1 Introduction

Since Ritter (1991) and Loughran and Ritter (1995) reported the long-run underperformance of newly public firms, it has remained a puzzle. Prior work has examined several possible explanations for this phenomenon.[28] To the best of our knowledge, no work has yet addressed the impact of industry peers' actions on firms' post-IPO pricing despite evidence that industry peers' actions affect firms' stock prices (Hou and Robinson, 2006; Irvine and Pontiff, 2009; Hoberg and Phillips, 2010). In this paper, we focus on one important set of industry peer actions: their going public decisions. Specifically, we examine whether subsequent peer IPOs can explain the stock underperformance of recently public incumbents.

The idea that financial market entry by new firms affects the value of incumbent firms is not novel. Existing studies by Akhigbe, Borde, and Whyte (2003), Braun and Larrain (2009), Hsu, Reed, and Rocholl (2010), and Spiegel and Tookes (2019) all investigate the impact of IPOs on the values of public incumbents. While they disagree about the cause of the price impact of entry by IPOs, each finds that the IPOs negatively impact the value of incumbent firms. Akhigbe et al. and Hsu et al. define incumbents as all publicly traded firms in an IPO's industry, regardless of listing age, and attribute the negative price impact to peer IPOs' competitive effects. Braun and Larrain (2009) look at new entry via IPOs in emerging markets and posit that a supply effect affects all public incumbents, even for firms outside the new entrant's industry. Lastly, Spiegel and Tookes (2019) document that rivals' IPO competitive effects and industry-wide downward trends both play roles in incumbents' reactions to rivals' IPO decisions. However, the focus of this

[28] See, *inter alia*, Brav and Gompers, 1997; Carter, Dark, and Singh, 1998; Das, Guo, and Zhang, 2000; Field and Lowry, 2009; Loughran and Ritter, 1995; Da, Engelberg, and Gao, 2011; Titman, Wei, and Xie, 2004; Carlso, Fisher, and Gimmarino, 2004; Lyandres, Sun, and Zhang, 2008; Brau, Couch, and Sutton, 2012.

paper is not as broad as the studies above, as we focus on newly public incumbents (*hereafter "NPIs"*), which we define as firms that go public in the past three years.

We focus on NPIs because they are small relative to seasoned public incumbents and are more likely to share similar investment opportunities with peers that go public subsequently. Further, the rapid expansion and changes in the information environment that NPIs undergo after IPOs makes them more sensitive to unexpected shocks (Iliev and Lowry, 2019). As a result, the entry of a new industry peer via IPO is relatively important for NPIs. We hypothesize that the cumulative negative shocks from industry peers' IPOs drive down NPIs' stock prices, leading to stock underperformance and find that industry peers' IPO filings account for a substantial portion in NPIs' long-run stock underperformance.

We begin by showing that NPIs' stock prices react negatively and immediately to industry peers' IPO filings. We find that the three-day cumulative abnormal returns (CARs) around industry peers' IPO filing dates range from -6 bps to -31 bps using various methodologies for measuring event abnormal returns. Whether we employ the models suggested by Brown and Warner (1985) and Long (1990) or simply subtract the returns of portfolios formed on the basis industry and size, or market-to-book and size match and all three-day CARs are negative and statistically significant. The NPIs' reactions to industry peer IPO filings support our hypothesis that peer issuance activities have a negative effect on NPIs' post-IPO stock prices. We note that Akhigbe, Borde, and Whyte's (2003), who define incumbents as all firms in the Compustat database report that on average industry peers' IPOs, have no impact on incumbent firms. Our results are consistent with our argument that NPIs are indeed more vulnerable than mature incumbents to industry-follower IPO activities.

After establishing the average announcement effects of peer IPO activities, we explore the cross-sectional variation in CARs to analyze which NPIs are more affected by peer IPO activity. The peer-issuance activity explanation generates four interesting predictions. First, industry-follower IPOs have a more negative effect on smaller NPIs. This is predicated by Hsu, Reed, and Rocholl's (2010) finding that small incumbents experience more pronounced negative stock reactions when peers announce IPOs. Second, the negative impact of peer IPO activity should be greater for NPIs that have more investment opportunities in time to the peer's entry. The idea is that NPIs with more investment opportunities have more value to lose after peers' IPOs, since NPIs and the subsequent industry peers may share investment opportunities. We thus expect that NPIs' investment opportunities should be negatively associated with industry-follower IPO filing CARs. Third, peer entry during the industry downturn should be more value-destroying than industry upturns because competition intensifies as the industry-level investment opportunities become limited. Lastly, ex-ante, investors in competitive industries do not fully incorporate the negative externality of industry competition on cash flows and stock returns (Hoberg and Phillips, 2010). In this case, we expect that NPIs should respond more negatively upon peers' IPOs in the competitive industries.

We examine the four predictions above by estimating cross-sectional regressions of NPIs' CARs on various attributes. Notably, we include two sets of variables: 1) the initial attributes including sales, market-to-book ratio, and leverage at the time of NPIs' IPOs, and 2) the change in attributes from NPIs' IPOs to each peer IPO quarter. To alleviate the concern that industry investment opportunities endogenously drive peers' IPO decisions and NPI's stock performance (Spiegel and Tookes, 2019), we include industry-by-month fixed effects to remove the time-varying industry-level shocks. We also control for the peer IPO fixed effects to account for any difference in industry followers' attributes.

The results reveal that NPIs that are small at the time of IPOs react more negatively to industry follower IPO filings, which corroborates the findings in Hsu, Reed, and Rocholl (2010) that small NPIs are more vulnerable to peers' IPOs. Interestingly, controlling for the initial size, NPIs that expand rapidly (as measured by the change in sizes) experience greater value losses upon peers' IPO filings. One possible explanation is that IPOs facilitate industry followers' competition with high growth NPIs. Second, NPIs with more investment opportunities respond more negatively to peers' IPOs, consistent with the notion that IPOs can help industry peers grasp incumbents' investment opportunities. Third, NPIs' stock reactions to peer entry indeed depend on the concurrent industry conditions: the negative reactions are more pronounced during industry downturns and in competitive industries. Overall, industry followers' IPOs negatively affect NPIs' pricing, and such effects cannot be explained by either time-varying industry shocks or the timing of industry followers' IPOs.

We provide additional evidence of the impact of peer issuance activities on NPIs' long-term stock returns using a "what-if" methodology. We begin by constructing the standard 3-year post IPO buy-and-hold return (BHAR) as in (Loughran and Ritter 1995). We then recalculate the 3-year BHAR excluding NPIs' stock reactions to peer IPO filings. Specifically, whenever an industry peer files an IPO, we set the NPI's returns to the returns on a benchmark portfolio for the three-day period centered on the peer's filing date. This effectively sets the NPI's abnormal return to zero on the dates corresponding to peer entry. We find that industry-follower IPO filings explain approximately 60% of NPIs' 3-year underperformance—the average buy-and-hold abnormal returns (BHAR) is reduced from -9.36% to -3.71%.

The evidence that industry-follower IPOs have a disproportionate impact between small and large NPIs indicates that peer IPO activities should explain a larger portion of underperformance in small NPIs. Indeed, the difference is more pronounced among small

NPIs: BHAR changes from -18.89% to -7.83% for NPIs with initial sales below $100 million, while there is no significant reduction in BHARs for NPIs with sales above $100 million after excluding the peer impact. Additionally, we verify these findings using the calendar-time portfolio approach in Mitchell and Stafford (2000). Collectively, these results show that industry-follower IPO activities have a negative and significant impact on NPIs' long-term stock performance and such effects are more pronounced among small NPIs.

This study contributes to the literature in the following two aspects. First, it adds to the extensive literature on the new issue puzzle by considering industry peers' actions. Existing studies primarily focus on incumbents' market timing incentives (Loughran and Ritter, 1995), IPO participants' characteristics (Carter, Dark, and Singh, 1998; Brav and Gomper, 1997), and incumbents' post-IPO activities in explaining NPIs' stock underperformance. For example, Lyandres, Sun, and Zhang (2008) argue that the post-IPO investment activities help to resolve the new issue puzzle. Nevertheless, firms do not operate in isolation, and we extend this literature by showing that peer activities explain a substantial portion of NPIs' long-run underperformance. Additionally, unlike other explanations that do make distinctions between small and large NPIs, our peer issuance activity story predicts that NPIs with small initial sizes are more sensitive to peer IPO activities and should exhibit more severe underperformance. This evidence accommodates Ritter's (2011) observation that long-run post-IPO underperformance only exists among small NPIs.

Second, this paper also relates to the broad literature regarding how industry rivals affect incumbents' stock pricing. For example, prior literature has uncovered the evidence that industry peers' bankruptcies (Lang and Stulz, 1992), acquisition decisions (Song and Walkling, 2000), and financing decisions (Hsu, Reed, and Rocholl, 2010; Bradley and Yuan, 2013) influence incumbents' stock performance. Our paper differs by focusing on the newly public incumbents and provide further evidence that newly public firms are more sensitive to the unexpected shocks from industry peers' IPO decisions. This evidence is in line with the recent studies that newly public firms are fundamentally different from other seasoned public firms (Field, Lowry, and Mkrtchyan, 2013; Iliev and Lowry, 2019).

2.2 Literature Review

2.2.1 Evidence Regarding NPIs' Stock Underperformance

The new issue puzzle has drawn much attention from researchers since Ritter (1991) and Loughran and Ritter (1995) document stock underperformance following newly public firms. Earlier studies center on whether the new issue puzzle is an outcome of market timing or a risk mismeasurement problem. The market timing hypothesis posits that firms issue overvalued equity, and investors underreact to the market timing incentives. In contrast, Brav and Gompers (1997), Eckbo, Masulis, and Norli (2000), and Eckbo and Norli (2005) provide evidence that the new issue puzzle is consistent with standard asset pricing models. However, it remains an unsettled question of whether the long-run underperformance of IPOs is due to investor optimism or risk mismeasurement problems (Eckbo, Masulis, and Norli, 2007). Using 7,314 U.S. IPOs from 1980 to 2008, Ritter (2011) reports that the long-run underperformance of IPOs is approximately -7.1%, after matching IPOs with control firms.

Regardless of whether the evidence for the long-run underperformance of IPOs reflects market inefficiency, researchers have uncovered several factors that help explain this phenomenon. The first stream of the literature concentrates on the predictive factors at the time of IPOs. For example, prior research finds that IPOs conducted by more prestigious underwriters (Carter, Dark, and Singh, 1998), with venture-backing (Brav and Gomper, 1997), more institutional investors (Field and Lowry, 2009), high initial analyst coverage (Da, Engelberg, and Gao, 2011), and more underwriter centrality (Bajo, Chemmanur, Simonyan, and Tehranian, 2016) outperform other IPOs. However, the selection between IPO firms and participants makes it difficult to draw a causal conclusion between these initial IPO characteristics and NPIs' subsequent stock underperformance. Another stream of literature provides plausible explanations by focusing on NPIs' own post-IPO real operation. For example, existing studies have uncovered the post-issuance investment activities (Carlson, Fisher, and Giammarino, 2004, 2006; Titman, Wei, and Xie, 2004; Lyandres, Sun, and Zhang, 2008), follow-on financings (Billett, Flannery, and Garfinkel, 2011; Huang and Ritter, 2020), and post-IPO acquisitions (Brau, Couch, and Sutton, 2012) can account for NPIs' stock underperformance.

However, all the studies above assume that the new issue puzzle is independent of the activities of an NPI's industry peers', despite the fact that there is a literature showing that industry peers' actions and conditions affect a firm's stock returns (e.g., Hou and Robinson, 2006; Hoberg and Phillips, 2010). In this study, we relax this assumption and find that industry-follower IPO filings can explain a significant portion of the new issue puzzle. More importantly, none of the prior studies make a distinction between small and large NPIs,[29] while Ritter (2011) reports that the long-run underperformance of IPOs only pertains to IPOs with small initial size.[30] The peer-issuance-activity story can accommodate this new evidence, as it predicts that NPIs' initial sizes matter in their long-run underperformance.

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[29] Some existing papers are hard to reconcile with this evidence. For example, it is unclear why post-IPO acquisitions can explain the new issue puzzle only in relation to small IPOs and not to large ones, given that large firms are usually worse bidders than small firms (Moeller, Schlingemann, and Stulz, 2004).

[30] Notably, Ritter (2011) splits the sample into two groups by pre-IPO sales, defining a 0–49.999-million-dollar group and an above 50-million-dollar group, and finds that there is no evidence of long-run underperformance in the large IPO group.

2.2.2 Why are Newly Public Incumbents Vulnerable to Peer IPOs?

Prior studies have uncovered that firms' stock prices and cost of capital are materially dependent on industry peers' actions and financial health. For example, Hou and Robinson (2006) document that firms within competitive industries earn higher expected returns because investors require compensation for bearing the innovation and distress risk. Hoberg and Phillips (2010) argue that investors do not fully incorporate the negative externality of industry competitions. Valta (2012) finds that the loan spread is higher for more competitive industries. Lastly, incumbents experience substantial value losses during industry downturns when industry rivals have a larger portion of long-term debt maturing shortly (Carvalho, 2015). Given the importance of peers' actions on incumbents' stock performance, it is surprising that no studies have examined the role of peer effects in post-IPO stock performance.

In this paper, we focus on one particular event, industry peers' IPOs, on newly public incumbents' stock performance. Newly public incumbents are fundamentally different from seasoned public firms in several ways. First, NPIs are small by nature and are more informationally opaque because of the limited financial history as public firms. Also, managers of NPIs also typically have limited experience in coping with public market investors and analysts (Field, Lowry, and Mkrtchyan, 2013). Consequently, the rapid expansion and changes in the information environment that NPIs undergo after IPOs makes them more sensitive to unexpected shocks (Iliev and Lowry, 2019). Therefore, we expect that NPIs should be more sensitive to industry peers' actions than seasoned public firms.

Recent literature has shown that peers' IPOs can affect the pricing of listed stocks. Specifically, peer IPOs can have competitive effects, information effects, and supply effects on incumbents' stock performance. All three channels predict that newly public incumbents should react more negatively than seasoned public incumbents to industry-follower IPOs.

First, the competitive effects of peer IPOs predict that NPIs should respond more negatively than seasoned public incumbents to industry-follower IPOs, and the effects should depend on the relative size of peer IPOs and incumbents. Studying 2,493 IPOs between 1989 and 2000, Akhigbe, Borde, and Whyte (2003) analyze the impact of IPOs on rivals' stock prices and find that the average effects are not statistically different from zero. They argue that valuation effects are insignificant because the competitive effects of peer IPOs offset the information effects. A follow-on study by Hsu, Reed, and Rocholl (2010) documents the competitive effects of "influential" IPOs. Specifically, they select the 134 IPOs with the largest proceeds and show that the stock prices of incumbents in the same industry react negatively (positively) to IPO filings and issuances (withdrawals) made by these relatively large entrants. Since NPIs are small firms by nature, each industry-follower IPO is large relative to the recently public incumbent and thus any IPO should exert a larger negative impact on same-industry NPIs.

Second, industry-follower IPOs may contain information about the whole industry, and such information can be either positive or negative. On the one hand, peers' equity financing behaviors indicate there are ample investment opportunities in the industry. On the other hand, peers' equity financing may signal the overvaluation of the whole industry (Bradley and Yuan, 2013). Nevertheless, Spiegel and Tookes (2019) argue that industry-followers' IPOs foreshadow industry-wide downtrend, suggesting that industry-follower

IPOs on average deliver unfavorable industry-wide information.[31] Therefore, the information channel should also predict an average negative reaction by NPIs than seasoned public firms.

Lastly, Braun and Larrain (2009) document that the introduction of a new IPO may have supply effects on listed firms, which even among firms from different industries. Notably, Braun and Larrain (2009) investigate the introductions of large IPOs in 22 emerging markets and find that an IPO affects all the public firms' stock prices permanently. Braun and Larrain (2009) also predict that stocks that are small and that comove more with the IPO firms should be affected more by supply effects.[32] Nevertheless, Braun and Larrain's (2009) model builds on the assumption of downward-sloping demand curves, and they explicitly acknowledge that supply effects may not exist in a developed market such as the U.S. stock market. Therefore, the supply effects of industry peers' IPOs in our sample is an empirical question.

Any or all of these channels support our argument that industry-follower IPO filings should, on average, reduce the value of an NPI. Therefore, it is plausible that peer issuance activities can account for the NPIs' post-IPO underperformance.

2.3 Sample Selection and Data Description

We construct two IPO samples from the Securities Data Company (SDC) New Issue Database: an NPI sample contains all completed IPOs between 1983-2015 and an IPO filing sample contains all completed and withdrawn IPOs between 1983-2018.[33] We first extract

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[31] This argument is also consistent with the anecdotal evidence that when Uber filed its IPO, Lyft's stock price dropped by 11%. Please see: https://www.ft.com/content/504acaf2-5bcf-11e9-9dde-7aedca0a081a.

[32] Untabulated results show that an NPI tends to move with a newly public firm portfolio and such comovement is larger than its comovement with the market or industry portfolio.

[33] We start from the year 1983 because this is the first year SDC starts disclosing the filing information (Lowry, Michaely, and Volkova, 2017). Our NPI sample ends in 2015 to leave three years over which to assess the 3-year post-IPO stock performance.

all IPOs and the relevant IPO information between 1983 and 2018, including venture capital backing, issue proceeds, and so on from the SDC. Following Ritter (2020a), we make corrections for the SDC variables such as the SIC codes, the book value of equity, and sales[34]. Consistent with the prior studies, units offers, ADRs, REITs, limited partnerships, SPACs, closed-end funds, non-US, and IPOs with prices below $1 are dropped from the sample. In total, there are 11,977 IPOs over the period 1983-2018, including 9,373 completed and 2,604 withdrawn IPOs[35].

We construct the NPI sample by keeping completed IPOs between 1983-2015, which contains 9,096 NPI firms. To remain in the NPI sample, an IPO must have CRSP information at the end of the IPO month and a non-missing book value of equity.[36] These criteria leave us with 8,863 NPI firms dating from 1983 to 2015. To assign industry peers to the Fama-French 48 industries based on the historical SIC codes. We first use the SIC code from Compustat and replace it with the SIC codes from CRSP if it is missing in Compustat. We do so because Kahle and Walkling (1996) argue that SIC codes are more accurate on Compustat than CRSP. Any further missing values we replace with the SIC codes on SDC.

One thing worth noting is that our NPI sample contains 171 NPI firms that do not have industry-follower IPOs in the following three years, among which 115 of them do not have available Fama-French 48 industry codes. We retain them in the NPI sample to avoid

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[34] We thank Professor Jay Ritter for all of the data he provides at https://site.warrington.ufl.edu/ritter/ipo-data/.

[35] The withdrawal rate equals 22.74%, which is comparable with the 19.79% IPO withdrawal rate in Dunbar and Foerster (2008).

[36] Following prior literature, the book value of equity comes from 1) the post-issue book value of equity on SDC and 2) the book value of equity reported for the nearest quarter after the IPO; further missing values are substituted for by the pre-IPO book value of equity on SDC plus the proceeds amount.

introducing additional sample selection bias. Moreover, we do not require NPIs to have non-missing filing dates.[37]

To obtain the peer IPO filing sample, we use both completed and withdrawn IPOs and remove 397 peer IPOs with missing filing dates or missing Fama-French 48 industry codes. Also, multiple industry peers can file IPOs on the same day, we thus further drop 1,078 industry peers that file IPOs on the same day. In total, the whole peer IPO filing sample contains 10,502 industry peers' filings.

Table 2.1 summarizes the statistics regarding the NPI sample. The average first-day underpricing equals 17.54%, the median firm age at IPO is eight years, and the proportion of VC-backed IPOs is 34%; these statistics are very similar to the prior studies (e.g., Ritter, 2011). Additionally, the average market-to-book ratio of firms in our NPI sample is approximately 3.14, which is consistent with the fact that IPOs tend to be firms with growth opportunities.

Overall, 8,692 NPIs have at least one industry-follower IPO filing in the following three years (or before delisting dates). The mean (median) of the number of industry peer filings is 71.85 (45). Figure 2.2 plots the mean and median number of industry peer filings in each of the three years following an NPI's IPO. It shows that the number of industry peers decreases over the three years after NPIs' IPOs. For example, the average numbers of industry filings are 29.5, 21.9, and 19.0 for years 1, 2, and 3, respectively.

[37] We retain 272 NPIs with missing filing dates.

2.4 Newly Public Incumbents' Reactions to Peer IPO Filings

In this section, we present the evidence from the event study and show that industry peer IPO filings have a negative and significant impact on NPIs' stock prices. Additional tests explore the determinants of the impact of industry peers' IPOs.

2.4.1 Newly Public Incumbents Stock Reactions

We first examine the effects of industry peer IPO filings on the newly public incumbents' stock prices using several event study approaches. For each NPI we create a three-day event window every time that NPI has an industry peer file for an IPO. We center the three-day event window centered on the filing date of the IPOs. We concentrate on filings rather than actual issuances because filings convey the first news of possible entry. If there are multiple industry peer filings on the same day, we treat that as a single-entry event in the event studies. Each NPI will have as many event windows as there are industry-peer filings in the three-year period after the NPI goes public.

Our first event studies use the methodology in Brown and Warner (1985). For each industry peer's IPO filing date, we set the estimation period as calendar days (-365, -30) relative to the filing date (day 0) and require that the NPIs have at least 30 observations in the estimation period to measure the betas. In each event's estimation period, we then adopt the market-model method and estimate the market beta $\widehat{\beta_i}$ and intercept $\widehat{\alpha_i}$ for each NPI. The CARs are the cumulative 3-day abnormal returns from the following estimation:

$$AR_{i,t} = R_{i,t} - \widehat{\alpha_i} - \widehat{\beta_i} R_{m,t}, t \in (-1, +1) \tag{2.1}$$

One disadvantage of this approach is that we lose observations of IPO industry peers' filings if these events are within 30 trading days of NPIs' going public. However, since we find that early-stage NPIs are more vulnerable to industry peer IPO effects in the following section, losing these observations will make it harder to obtain significant results.

Second, following Long (1990), we apply the numeraire portfolio approach, which allows us to retrain filing events that occur within the first 30 days. Specifically, the numeraire-dominated returns of stock j for the period (t-1, t] are:

$$AR_{i,t} = \frac{1 + R_{j,t}}{1 + R_{N,t}} - 1, t \in \left(-1, +1\right) \tag{2.2}$$

Where, $R_{j,t}$ is stock j's return on (t-1, t), and we use both value-weighted and equally-weighted market returns as $R_{N,t}$, the numeraire portfolio.

Finally, calculate abnormal returns using the returns of control firms as measures of expected returns. We select firms that have been public for at least five years. This provides some evidence on the effect of firms' listing age on the impact of peer entry. We use two separate sets of control firms. For the industry and size matched controls, we match each NPI to the firm in the same Fama-French 48 industry that has the closest market capitalization measured at the end of the NPIs' IPO months. Likewise, we also match each NPI with a mature public firm of a similar size and a market-to-book ratio. We also add back the delisting returns if an NPI delists, and if the control firm delists, we replace it with a second or a third control firm. The control firms in the size and market-to-book ratio match are the same in the buy-and-hold abnormal return approach in Section 5. Here the abnormal return is measured as

$$AR_{i,t} = R_{i,t} - R_{c,t}, t \in \left(-1, +1\right) \tag{2.3}$$

The daily abnormal returns are summed to form a three-day cumulative abnormal return $\left(CAR_{i,k}\right)$ for each of the N_i^{PE} peer filing events in the three year period following each NPI's IPO. We then calculate

$$\overline{CAR_i} = \frac{1}{N_i^{PE}} \sum_{k=1}^{N_i^{PE}} CAR_{i,k} \tag{2.4}$$

to measure the average impact of industry-peer filings for each NPI.

Table 2.2 describes the evidence from the event studies conducted over the three-year period following each NPI's IPO. In total, there are 8,692 NPIs with industry peer IPO filings in the following three years, and the mean (median) of industry peers' filings is 71.85 (45). Thus, there should be 8,692*71.852 = 624,537 filings in Table 2.2. However, the difference in observations is due to missing returns in CRSP or insufficient observations to estimate the market betas.

Panel A and B in Table 2.2 report $CAR_{i,k}$ and $\overline{CAR_i}$, respectively. For each event study method the average pooled $CAR_{i,k}$ is negative and significant, and $CAR_{i,k}$ ranges from -0.063% to -0.310%, indicating that investors in NPIs respond negatively to industry peers' IPO filings. As for $\overline{CAR_i}$, using Brown and Warner's (1985) methodology, on average, an industry peer's IPO filing are associated with a -0.258% decrease in NPI's stock prices. Rows (3) and (4) report the evidence using Long's (1990) methodology. The magnitude of $\overline{CAR_i}$ when the equally-weighted market returns serves as the numeraire portfolio are two times large (-0.210%). Rows (5) and (6), present estimates of $\overline{CAR_i}$ when we use control firms. $\overline{CAR_i}$ is -0.164% when an NPI is matched to a mature industry peer of similar size, and -0.143% when matched to a mature firm with similar size and market-to-book. The results in row (5) suggests that NPIs are more vulnerable to industry peer IPO filings than are more mature public incumbents. Overall, industry peers' IPO filings have a negative impact on NPIs' stock performance.

The results above are based on filings of peer firms that both completed and withdrew their IPOs. Prior studies report positive and significant $CAR_{i,k}$ upon industry peers' IPO withdrawals (Hsu, Reed, and Rocholl, 2010). If an NPIs' negative abnormal return upon filing is offset by a positive return upon an industry peer withdrawal, then the results in Table 2.2 overstate the impact of peers' IPO activities on NPIs' stock prices. To address this concern, for each peer firm that withdraws it IPO filing we calculate $CAR_{i,k}$ for the withdrawal date and compare them to the $CAR_{i,k}$ for that peer's filing date. Table 2.3 shows that NPIs experience negative $CAR_{i,k}$ on the filing dates of peers who eventually withdraw ($CAR_{i,k}$=-0.623%). It also shows that the $CAR_{i,k}$ on the withdrawal dates is small (0.032%) and statistically insignificant (p-value: 0.27) The withdrawal date $CAR_{i,k}$ do not offset filing date $CAR_{i,k}$ for peers who eventually withdraw. Thus, we keep all IPO filings regardless of actual issuance decisions in the following section.

2.4.2 Three-year Aggregated Impact of Industry Peers' IPOs

In the previous section we used event study methodologies to estimate the size and statistical significance of the impact of peer entry on the stock price of NPIs. The estimated average announcement abnormal returns are negative and statistically significant but appear to be small relative to estimates of three-year post-IPO performance. For each NPI, the total impact of peer entry is given by the aggregated abnormal returns over all peer filings or $N_i^{PE} \times \overline{CAR_i} = \sum_{k=1}^{N_i^{PE}} CAR_{i,k}$.

Table 2.4 reports the evidence on the of NPI's aggregate $CAR_{i,k}$. Independent of event sturdy methodology the average and median aggregated $CAR_{i,k}$ are negative and significant at 1%, indicating that the cumulative shocks from peers' IPO filings indeed decrease NPIs' stock performance. For example, the average aggregate $CAR_{i,k}$ measured using Brown and Warner's (1985) methodology are -19.651% and -12.496% for value-weighted and equally-weighted, respectively. This magnitude is economically large compared to Ritter's (2011) evidence that the 3-year underperformance of NPIs is approximately -7.1%, obtained using control firms of similar size and with similar market-to-book ratio. When we employ similar benchmarks to calculate $CAR_{i,k}$ (Row (5) (size-industry adjusted), and Row (6) (size-market to book adjusted)) the average aggregate $CAR_{i,k}$ of -9.015%, and -7.639%, are closer to the estimates reported in Ritter (2011). The evidence suggests that NPIs suffer more from industry peers' IPO filings than mature firms of similar size and with similar market-to-book ratios.

2.4.3 Cross-Sectional Determinants of Peers' IPO Filing CARs

In this section, we explore the cross-sectional determinants of the $CAR_{i,k}$. The peer issuance hypothesis suggests that small NPIs should react more negatively to industry-followers' IPO effects because small incumbents experience large value losses due to peers' IPO competitive effects (Akhigbe et al., 2003; Hsu et al. 2010). Additionally, small NPIs tend to invest aggressively and expand rapidly after being public, making them more vulnerable to industry-follower IPO effects. We thus expect that NPIs with small initial sizes should react more negatively to peer IPOs. In contrast, the size growth, as measured by the size changes from the NPIs' IPOs to the quarter before peers' IPOs, should be negatively related to $CAR_{i,k}$.[38] Second, we expect that NPIs with more growth opportunities are more likely to be predated as peers gain competitive advantage through IPOs, leading to greater value losses in NPIs. Therefore, both NPIs' levels and changes in growth opportunities should be negatively related to $CAR_{i,k}$. Third, the reason that NPIs exhibit negative long-term stock performance is that they are more susceptible to peers' filings than seasoned public incumbents. Hence, NPIs' listing age at the time of peer filing may also be a determinant of $CAR_{i,k}$. We use the logarithmic value of the number of days to proxy for listing age and expect the listing age to be positive and significant.

Furthermore, the peer issuance hypothesis predicts that peer IPO effects play different roles as industry conditions change. First, industry-follower IPO filings should be more value-destroying in industry downturns than in upturns. This is because during downturns, competition intensifies as industry investment opportunities become limited. We define the industry downturn dummy as one if the market-adjusted Fama-French 48 industry returns in the month before each peer filing is below the median of the prior year. Second, ex-ante, investors do not fully internalize the negative impact of industry competitions (Hoberg and Phillips, 2010). Consequently, industry rivals' IPO decisions should result in more negative price revisions in competitive industries. We thus creating a dummy variable for the competitive industry if an industry falls within the bottom tercile of the Herfindahl-Hirschman index based on sales in a specific year.

Regarding the control variables, we include the founding age, which is measured as the NPIs' firm ages at the time of IPOs, to rule out the possibility that our results are driven by NPIs went public at different life stages. We also add NPIs' IPO characteristics,

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[38] We measure size by the pre-IPO and post-IPO sales from SDC because we follow Ritter (2020b) to form different size groups in the long-term event study section. Missing values are replaced by the annual Compustat sales. The initial sizes are divided by 4 to be consistent with the other quarterly Compustat variable.

such as the percentage of primary share offered, underwriter ranking, whether an NPI was backed by VC, and the primary share amount. Furthermore, we create a dummy variable, Post, which equals one for NPIs that went public after the year 1998 and interact with the NPIs' VC dummy variable. We do so because Ritter (2011) shows that the positive relation between VC-backed IPOs and NPIs' long-term underperformance has reversed after in recent years. We include the interaction term between VC dummy and Post to examine whether VC-backed IPOs become more susceptible in recent years. Another concern is that industry-follower IPO filings are not random. For example, the expectation of worsened industry conditions may endogenously drive peers' IPO decisions and NPIs' stock reactions (Spiegel and Tookes, 2019). To address such an omitted variable problem, we include industry-by-filing-month fixed effects to absorb the time-varying industry conditions. We also add peer IPO fixed effects to address the concern that industry peers may differ in attributes. Lastly, we cluster the standard errors by NPIs to account for the correlation within a single NPI firm.

Table 2.5 summarizes the determinants of $CAR_{i,k}$.[39] In Column (1), we first analyze the cross-sectional regressions with NPIs' initial attributes and their IPO deal-level characteristics. NPIs' initial size (as measured by Ln(Sales)) and MB ratio are significant at the 1% level, consistent with our hypothesis that small NPIs and NPIs with more growth opportunities respond more negatively to peer IPO effects. In addition, listing age is positive and significant, suggesting that as NPIs season, industry-follower IPO filings have a less negative impact on their share prices. Furthermore, incumbents' leverage is statistically insignificant, which is inconsistent with the prior literature demonstrating that low leverage provides incumbents with strategic flexibility (Zingales 1998; Matsa 2011; Cookson 2017).

[39] Across all the specifications, we require non-missing values for all the variables in Column (2) to keep consistent sample sizes. Nevertheless, our results remain quantitatively and qualitatively similar if we remove these restrictions.

However, it is not entirely surprising given that the cash proceeds obtained from IPOs may relax NPIs' financial constraints temporarily. Lastly, the interaction between VC-backed IPOs and the Post dummy is negative and significant at 1%. This evidence indicates that the reversed evidence between VC-backed IPOs and long-run underperformance is driven by the fact that VC-backed IPOs are more vulnerable to industry peers' IPO filings in recent years.

Next, in Column (2), we include the changes in size, MB ratio, and leverage from the initial levels to the most recent quarter before each industry peer's IPO. Interestingly, the initial size becomes insignificant (p-value: 0.68). By contrast, the change in size (as measured by $\Delta \text{Ln(Sales)}_t$) is negative and significant at the 1% level, suggesting that after controlling for the initial size, NPIs that expand more rapidly after being public are more sensitive to peers' IPOs. One plausible explanation is that industry rivals' IPO decisions drive down the valuation of NPIs' existing expansion plans. Furthermore, $\Delta \text{MB Ratio}_t$ is negative and significant. This evidence is consistent with the notion that NPIs with more potential growth opportunities have more to lose to industry rivals. As expected, $\Delta \text{Leverage}_t$ is insignificant (p-value: 0.22). This is because many NPIs originally do not have access to the debt market.[40] Thus, the negative effects of increasing leverage can be offset by the positive effects of gaining access to the bond market.

Turning to Column (3), we further add NPIs fixed effects to explore the within-NPIs variation. In contrast to Column (2), Ln(Listing Age) is subsumed by other time-varying NPIs' attributes.[41] This evidence does not support the contention that as an NPI seasons, it will naturally become insensitive to peer IPO effects. Instead, Ln(Listing Age) only picks

[40] 25.90% of NPIs in our sample report zero or missing leverage in the first quarter.

[41] Ln(Listing Age) remains significant without the three time-varying NPIs attributes (P-value: 0.024).

up other time-varying attributes that make NPIs more sensitive to peers' IPOs.[42] Furthermore, ΔLn(Sales)$_t$, ΔMB Ratio$_t$, and ΔLeverage$_t$ are consistent with Column (2) after adding the NPIs fixed effects.

Lastly, we explore the impact of industry conditions on $CAR_{i,k}$ in Column (4). We replace the Industry-by-Month F.E. with the month F.E. and remove the Peer IPO F.E. because of the multicollinearity with the industry condition measures. Column (4) shows that the industry downturn dummy is negative and significant at the 1% level, consistent with the notion that NPIs experience more value losses to rivals' IPOs in a shrinking industry. As expected, the peer IPO effects are more pronounced among competitive industries, which is consistent with the peer IPOs' competitive effects in Hsu, Reed, and Rocholl (2010).

Overall, NPIs with small initial sizes, more growth opportunities, and experience high size growth respond more negatively to peer IPOs. Also, NPIs in shrinking and competitive industries amplify the peer IPO effects. Therefore, industry peer IPOs indeed negatively affect NPIs' stock pricings, which can not be explained by any time-varying industry trends or the timing of IPOs.

2.5 Industry Peer IPO Effects and The New Issue Puzzle

Section 2.4 documents that, on average, industry peers' IPO filings have a negative impact on NPIs' post-IPO stock returns. Because the long-run stock performance is simply cumulative short-run stock performance, in this section, we investigate the influence of industry peers on NPIs' long-run stock performance.

[42] Ln(Listing age) becomes insignificant when either ΔLn(Sales)$_t$ or ΔMB Ratio$_t$ is added in the model.

2.5.1 Buy-and-Hold Abnormal Return Approach

We use the buy-and-hold abnormal return approach (BHAR) in Barber and Lyon (1997) and follow Ritter's (2011) methodology to replicate the evidence of long-run underperformance of IPOs. We first create a potential matching sample by choosing all firms on CRSP that have been listed and do not conduct IPOs or SEOs in the past five years. Subsequently, for each NPI from 1983 to 2015, we retain matching firms that are ±30% of their market capitalization at the end of each NPI's IPO month. Next, for each NPI, we choose a firm that has the closest market-to-book ratio as the incumbent to serve as its control firm. There are 8,863 NPIs in the event sample, so we find 8,863 corresponding control firms. For the book value of equity numbers, following Ritter (2011), we use the post-issue book value of equity on SDC, and we replace missing values with the book value of equity reported on the nearest quarter after IPO. Further missing numbers are calculated using the reported pre-IPO equity book values plus the amount of the proceeds.

To mitigate the influence of delisting issues, following Loughran and Ritter (1995), we further require that, if an IPO firm delists before its anniversary date, its delisting return is added into its return, and we truncate its total return on that date. Moreover, if a control firm delists, its delisting return is added into its return, and we replace it with the next closest market-to-book control firm on the next day after the listing date. Similarly, if the second control firm delists, we replace it with a third one.

The long-run buy-and-hold abnormal returns are calculated as the NPIs' cumulative returns minus the control firms' cumulative returns over the same horizon.

$$BHAR_{0,3}^{i} = \prod_{t=1}^{3\times 365}\left(1 + r_t^i\right) - \prod_{t=1}^{3\times 365}\left(1 + r_t^B\right) \tag{2.5}$$

where $BHAR_{0,3}^{i}$ is the buy-and-hold abnormal returns for firm i over the 3 years following its IPO, r_t^i is the daily return of firm i on day t (excluding the first day), and r_t^B is the benchmark return.

Table 2.6 reports the evidence of long-run underperformance. On average, NPIs underperform their control firms. For the NPI sample, the average BHAR equals -9.364%. Following Ritter (2011) we also present evidence on the long-term underperformance stratified by the size of the NPIs at the time of their IPOs. We sort firms into groups based on revenues measured in constant 2016 purchasing power. We average pre-IPO sales from SDC and post-IPO sales measured at the end of the firm's first fiscal year on Compustat. Panel B and Panel C report the 2-group and 6-group results, respectively. Consistent with Ritter (2011) the results in Panel B show that long-run post-IPO underperformance is isolated to small NPIs whose BHAR is -18.890%. The three-year, post-IPO BHAR for large NPIs is 5.545%. This is consistent with the results from our analysis of $CAR_{i,k}$ in Table 2.5.

We provide more granular evidence by sorting the NPIs into six groups based on their initial sizes. We follow Ritter (2020b) and forms groups below 9.999m, 10–19.999 mm, 20–49.999 mm, 50–99.999 mm, 100–499.999 mm, and above 500 mm. Panel C reports the BHAR results following Ritter's (2020b) classifications. It shows that the evidence of underperformance only pertains to the top four groups with smaller initial sales, and the underperformance decreases monotonically by sales in the four groups from -4.777% to -33.085%. These results are consistent with Ritter's (2011) recent evidence that the post-IPO underperformance only exists in newly pubic firms with small initial sizes.

To examine whether NPIs' long-run underperformance is driven by industry peers' IPO filings, we next implement a "what-if" methodology to exclude the impact of industry peers' IPO filings. Specifically, for each NPI, we identify the IPO filing dates of its industry peers in the three years following its IPO and then set the NPI's stock returns of the three-day window (-1, +1) to be the control firm's returns. To illustrate, Table 2.A2 in the appendix depicts Fitbit's example of excluding the industry-follower IPO effects, where the red asterisks denote Fitbit's industry peer IPO filing dates. We remove the industry peer IPO effects by replacing the three-day NPIs' returns with the control firms' returns on each industry follower's IPO filing date.

Table 2.6 shows that the average BHAR decreases to -3.707%, indicating that industry peers' IPO filings account for a decrease of 60.412% [1-(-3.707%/-9.364%)] in 3-year long-run underperformance. More importantly, Panel B shows that the decline in BHAR comes mainly from the small NPIs. The average BHAR in the small NPIs group increases from -18.890% to -7.825%, while the average BHAR decreases in the large NPI group. Additionally, the reduction in BHAR for the small NPI group is statistically significant at 1% level. These results are consistent with the results for $CAR_{i,k}$ in Table 2.5 and the hypothesis that the post-IPO underperformance, especially for NPIs with small initial size, is affected by peer entry.

Ritter (1991) shows that IPO long-run underperformance remains an issue five years after IPOs. Table 2.7 reports the results in 5-year BHARs. Overall, industry peers' IPO filings explain up to 81.529% of the long-run underperformance. Similarly, the reductions are primarily driven by NPIs with small initial size.

2.5.2 Calendar-Time Portfolio Approach

As an alternative method of examining impact of peer entry on the long-run abnormal returns we employ the calendar-time portfolio approach (CTP) in Mitchell and Stafford (2000). We follow the prior literature and use monthly returns in the CTP approach

(Ritter and Welch, 2000). We construct our monthly returns with geometric sums of daily returns. We do this so that we can create a placebo monthly return where we remove NPIs' stock reactions around industry peers' IPO filing dates. Specifically, for each NPI we create two measures of its monthly return. The first is

$$r_{it}^{m} = \prod_{\tau^{m}} \left(1 + r_{i\tau}\right) - 1 \tag{2.6}$$

where $r_{i\tau}$ is the daily stock return for NPI firm i and τ_m is the number of days in a given month. This measure of monthly return exactly replicates the monthly return reported in CRSP.

The second measure is calculated as

$$r_{it}^{m} = \prod_{\tau^{m} \notin \tau^{p}} \left(1 + r_{i\tau}\right) \prod_{\tau^{p}} \left(1 + r_{\tau}^{B}\right) - 1 \tag{2.7}$$

where terms are the same as in (2.6), r_{τ}^{B} is the return on a benchmark portfolio, and τ_p represent days when there are peer entry. We use three different benchmark returns as replacements for peer entry returns: (i) the value weighted CRSP index, (ii) the return on mature firms matched by size and industry, and (iii) the return on mature firms matched by size and market-to-book. Equation (7) creates a monthly return that is purged of any abnormal returns associated with peer entry events.

Table 2.8 reports the CTP analysis. Panel A presents the results obtained using the compounded daily returns. Including an additional purged investment factor reduces the magnitudes and significance of the alphas, but it does not completely eliminate the significant negative post-IPO underperformance. Notably, alpha changes from -0.420 to -0.335 but it remains significant at 10%. This is consistent with Brau, Couch, and Sutton's

(2012) finding that the purged investment factor cannot completely absorb the alpha for IPOs. Nevertheless, excluding industry peers' IPO filings, either by using market returns or control firms, reduces the alphas more effectively than the purged investment factor. Specifically, replacing the returns on peers' three-day filing window by control firms' returns (Panel D) drives the alpha to insignificance (p-value = 0.14). Also, the magnitude decreases from -0.420 per month to -0.268 per month. All the evidence above suggest that negative impact of industry peer IPO filings make up a substantial portion of negative idiosyncratic returns following IPOs, and by excluding these effects, the NPIs' underperformance decreases substantially.

2.6 Conclusion

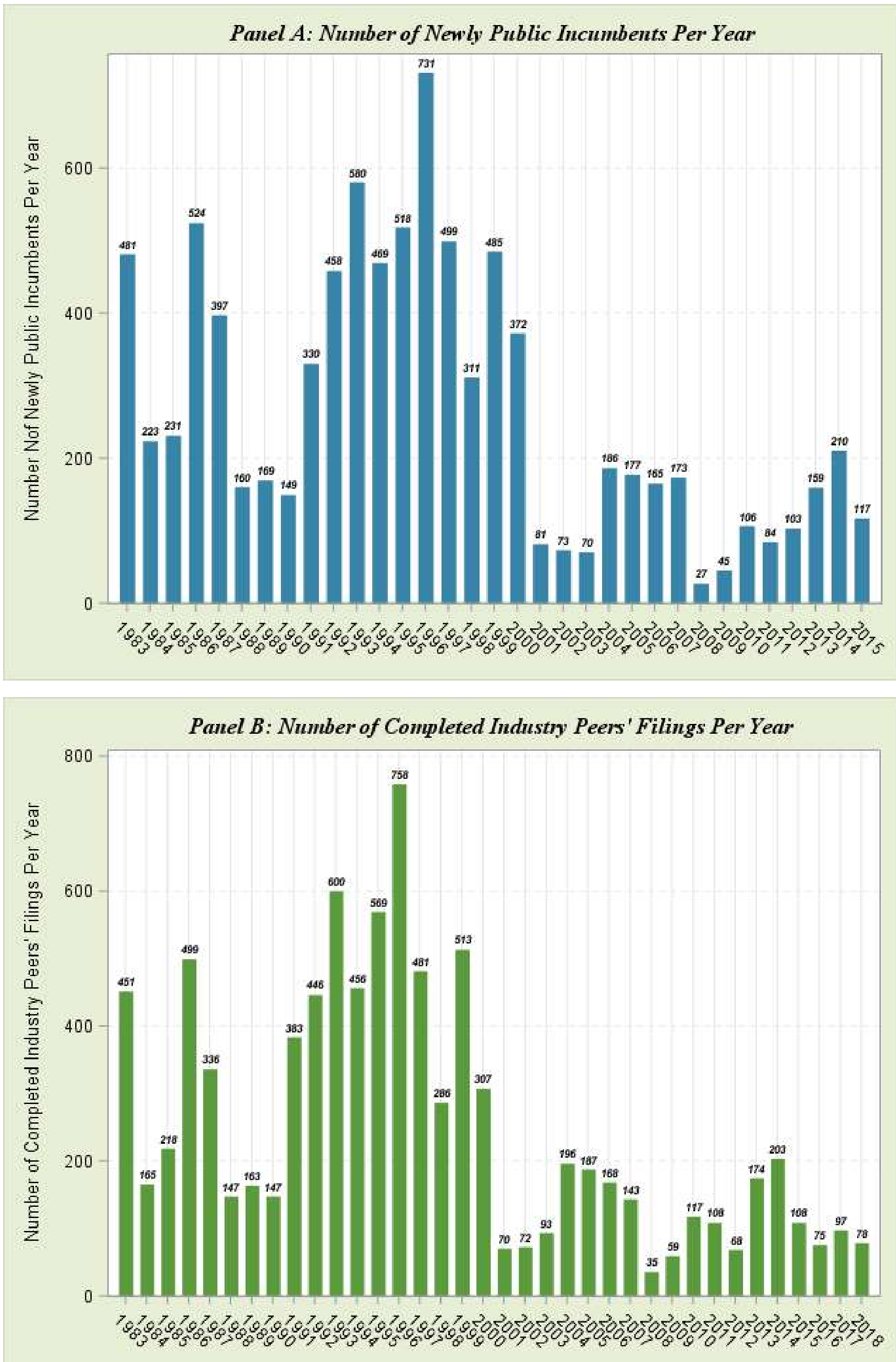
In this paper, we hypothesize that the cumulative negative shocks from industry-follower IPO filings contribute to the NPIs' stock underperformance. Following Hsu, Reed, and Rocholl (2010), we first verify that newly public incumbents, on average, react negatively towards industry peers' IPO decisions. We further show that such effects are more pronounced among small, high growth, and NPIs with more investment opportunities. We rule out the possibility that our results are driven by the unobserved time-varying industry shocks or the timing of peer IPOs. These results provide strong evidence that industry peers' IPO decisions have a crucial impact on NPIs' post-IPO stock performance.

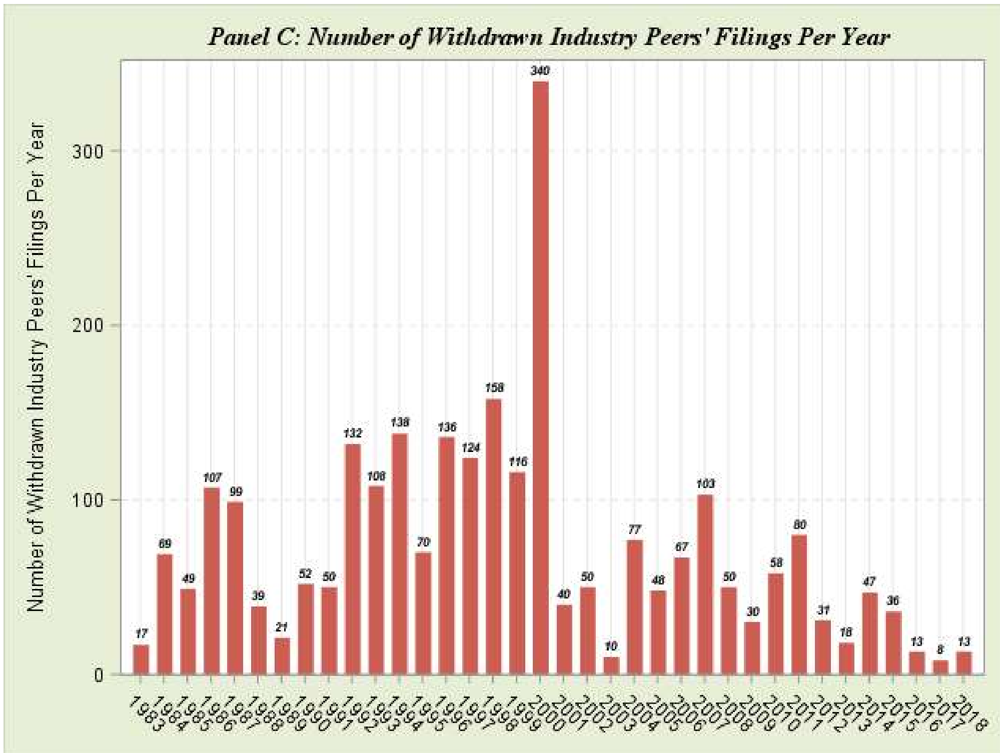
This study also complements the investment-based explanation of the new issue anomaly. One stream of the literature suggests that the post-issuance investment activities and the equity issuance anomaly are accordingly induced by marginal q (Cochrane 1991; Lyandres, Sun, and Zhang, 2008). The other stream of literature builds a causal relation between post-issuance investment and the new issue anomaly. For example, in the expansion options model in Carlson, Fisher, and Giammarino (2004, 2006), expansion options are riskier than the asset-in-place; thus, when firms exercise real options after equity financing, the overall riskiness decreases. Overall, the investment-based explanation implies that the new issue anomaly is closely related to incumbents' investment activities. Nevertheless, industry peer financing decisions can endogenously determine incumbents' investment activities. By showing that industry-follower IPOs can account for a large portion of NPIs' stock underperformance, our study highlights the importance of isolating the industry peer financing activities from the investment-based story.

One limitation of this study is that we consider only industry peers' IPO activities. It is plausible that other industry peers' behaviors, such as SEOs, earning announcements from seasoned pubic firms, might likewise have a strong impact on NPIs' post-IPO stock performance. Anecdotal evidence is that Snapchat's stock prices fell substantially and below the offer price after its IPO. This price decline is predominately driven by its competitor, Instagram, which released a similar product to Snapchat. Therefore, peer pressure from seasoned public firms can also negatively affect NPIs' long-term stock performance.

Lastly, this study opens doors for other interesting research questions. Notably, the event study section shows that NPIs react more negatively than seasoned public firms to peer IPO filings, which supports the recent work that suggests newly public firms are fundamentally different from seasoned public firms (Field, Lowry, and Mkrtchyan, 2013; Iliev and Lowry, 2019). Given this, one might ask what can be done to assist NPIs in accelerating the process? Additionally, we might also ask how we can help investors to incorporate future industry-follower IPO activities better. These questions would be worth exploring in future research.

Figure 2.1: Distributions of Newly Public Incumbents and Peers' IPO Filings





Panel C: Number of Withdrawn Industry Peers' Filings Per Year
Number of Withdrawn Industry Peers' Filings Per Year
0
100
200
300
17
69
49
107
99
39
21
52
50
132
108
138
70
136
124
158
116
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Figure 2.2: Number of Industry Peers' Filings by Year

This figure plots the number of industry peers' filings in year 1, 2, and 3 for each newly public incumbent. The blue and red bars represent the means and medians for the number of industry peers.

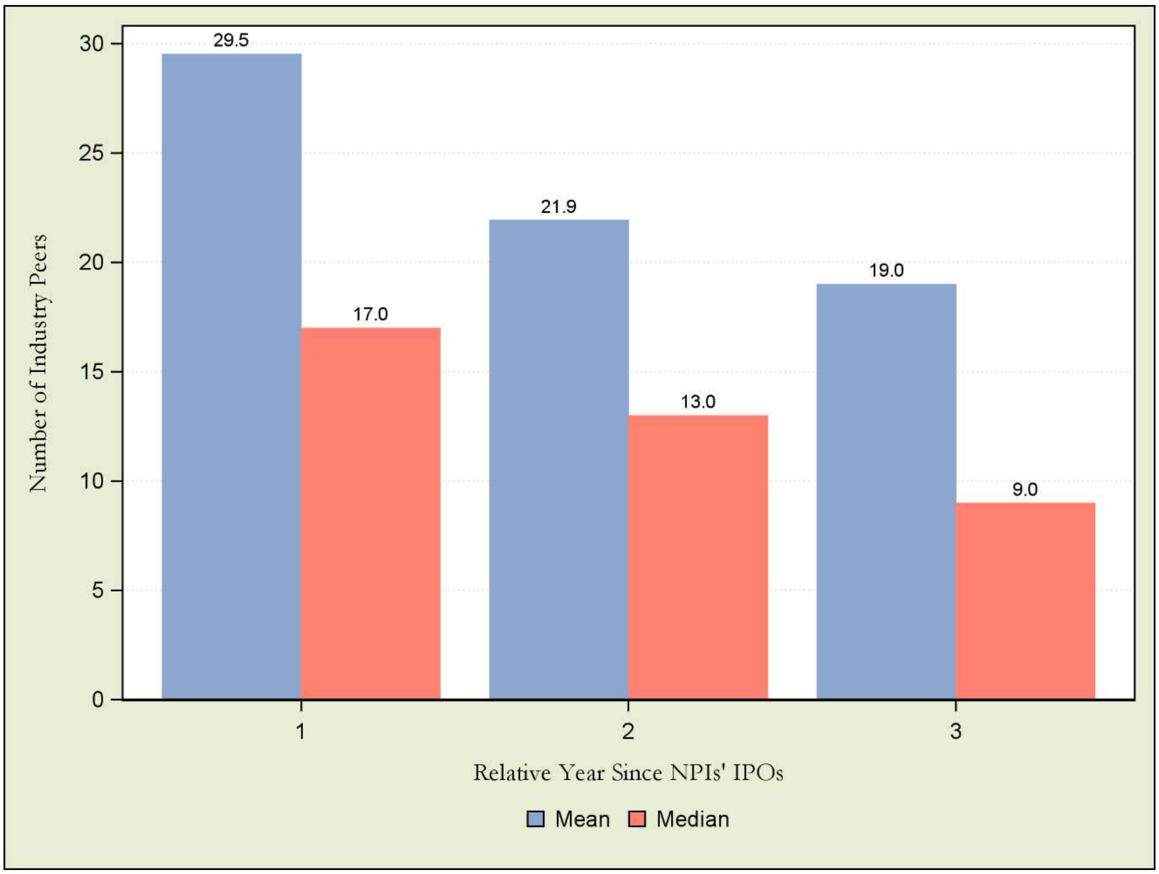
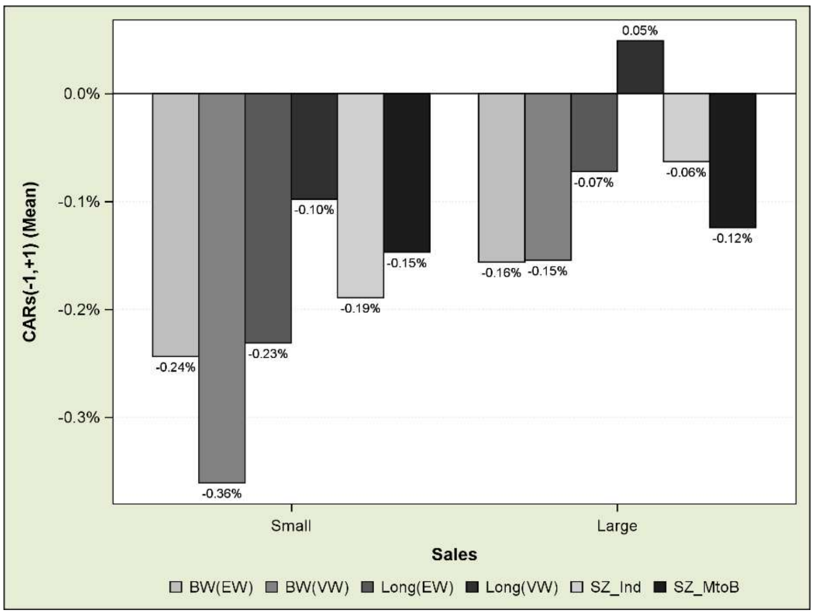


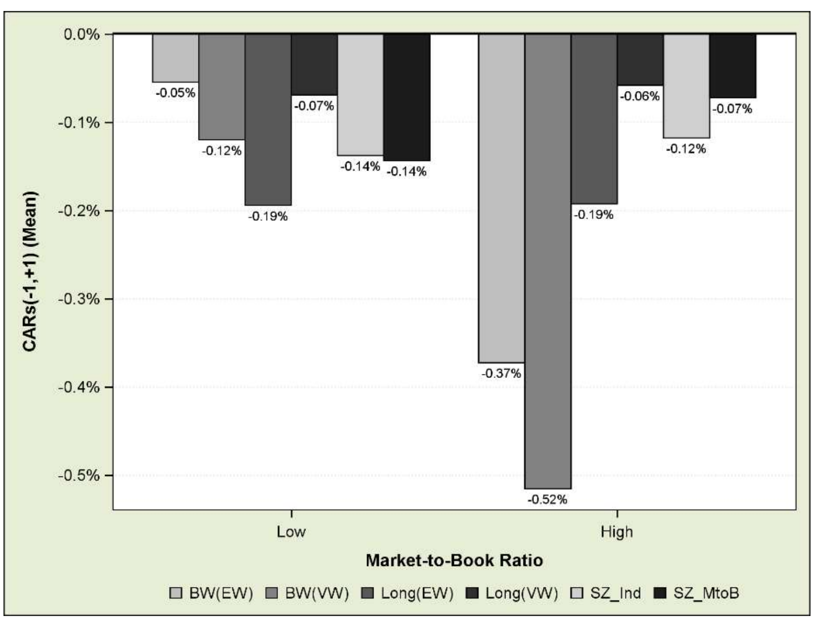
Figure 2.3: Stock Reactions to Peers' IPO Filings by NPIs' Attributes

This figure plots the three-day abnormal returns around industry peers' IPO filing dates. Panel A, B, and C show the CARs(-1,+1) by NPIs' initial CPI-adjusted sales (large and small represent sales above and below \$100 million), initial market-to-book ratio, and listing age (the number of years since IPOs). BW(EW) and BW(VW) represent Brown and Warner's (1985) methodology using equally-weighted and value-weighted market returns as benchmarks. Long (EW) and Long(VW) represents Long's (1990) methodology using equally-weighted and value-weighted market returns as numeraire portfolios. SZ_Ind and SZ_MtoB represent size-industry and size-MtoB ratio matches.

Panel A: By Sales



Panel B: By Market-to-Book Ratio



Panel C: By Listing Age

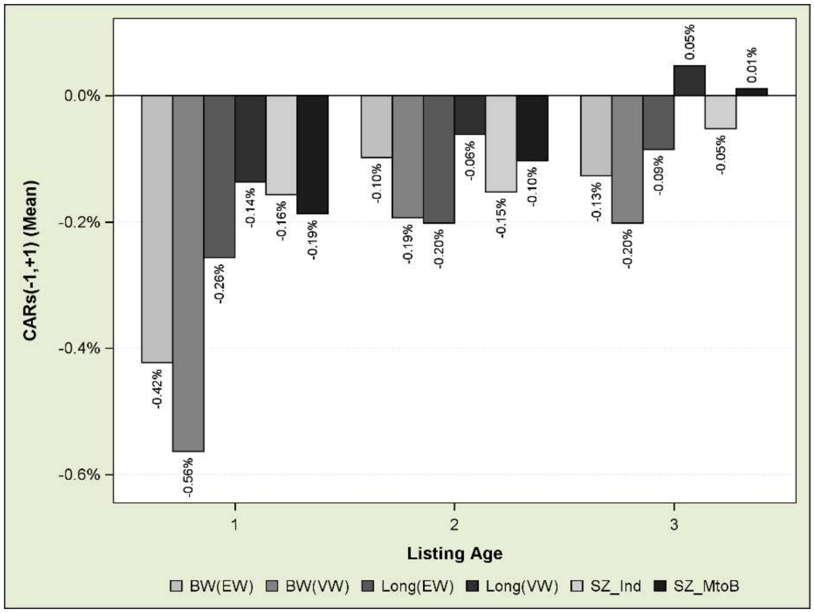


Table 2.1
Summary Statistics of NPIs, 1983-2015

This table reports the summary statistics of the newly public incumbent sample. The sample consists of 8,863 IPOs from 1983 to 2015. Unit offers, ADRs, REITs, closed-end funds, SPACs, small best efforts offers and IPOs with offer prices below $1 are excluded. Following Ritter (2020a), we correct mistakes in the SDC variables such as SIC codes, book value of equity, sales and etc. Market capitalization is measured as the share price multiplied by the number of shares outstanding at the end of NPIs' IPO months. For book value of equity numbers, we use the post-issue book value of equity on SDC and for the missing values, we replace them with the book value of equity reported on the nearest quarter after IPOs. Further missing numbers are calculated using the reported pre-IPO equity book values plus the amount of the proceeds. Firm age at IPOs is the age at which firms go public. IPO proceeds are the total amount of both primary and secondary shares an issuer raised from the IPO market. The first-day underpricing is calculated as: (IPO day closing price on CRSP - Offer price (available on SDC))/Offer price. For IPOs with missing values in IPO closing prices, we use the stock prices at the end of the IPO month. The missing values are due to missing stock prices on IPO date in CRSP. Venture capital backed (VC) is a dummy variable, which equals one if the IPO is backed by a venture capital company and equals zero otherwise. Underwriter rankings are the Carter and Manaster underwriter ranking. All variables are winsorized at 1% and 99% level.

Variable Name	N	Mean	Std Dev	P25	Median	P75
Market Capitalization (Millions)	8863	349.902	704.869	36.478	108.338	321.709
Tobin Q	8863	3.144	2.984	1.426	2.221	3.638
Firm Age at IPOs	8449	15.858	21.127	4.000	8.000	17.000
IPO proceeds (Millions)	8863	72.215	130.476	11.200	30.800	73.100
Percentage of Primary Shares Offered	8652	90.083	17.574	84.495	100.000	100.000
Primary Amount Offered (Millions)	8652	57.696	99.790	9.000	25.650	60.850
Total Amount Filed (Millions)	8255	69.439	111.123	13.300	32.500	80.000
First-day Underpricing	8863	0.175	0.348	0.000	0.066	0.231
Venture Capital Backed	8863	0.343	0.475	0.000	0.000	1.000
Sales (Millions)	8554	219.434	618.755	10.500	41.096	134.490
Underwriters' rankings	7950	7.188	2.249	6.001	8.001	9.001
Leverage	8127	0.167	0.211	0.004	0.068	0.273
Number of Industry-Follower IPOs	8692	71.852	82.423	20.000	45.000	86.000

Table 2.2

Newly Public Incumbents' Reactions to Industry Peers' IPO Filings

This table reports newly public incumbents' reactions to peers' IPO filings. $CAR_{i,k}$ is NPI i's stock reaction to each industry peer k's IPO filing. $\overline{CAR_i}$ is the average NPI i's stock reaction to all industry peers' IPO filings three years following NPI i's IPO. For each IPO between 1983 and 2015, an industry peers' IPO filing within 3 years following its IPO is classified as an event, regardless whether its peer completes the IPOs in the future. Row (1) and (2) report the event study results using Brown and Warner's (1985) methodology, which the benchmarks are CRSP VW and EW market returns. For each peer's IPO filing, market beta is estimated using daily returns between (-365, -30) and we require that there are at least 30 non-missing observations in the estimation period. Row (3) and (4) show the CAR(-1, +1) using Long's (1990) numeraire portfolio approach and the benchmark returns are CRSP VW and EW market returns, respectively. Row (5) reports the result by matching each IPO with an industry peer that belongs to the same Fama-French 48 industry and with the closest firm size but did not go IPOs in the prior 5 years. Row (6) reports the CAR(-1,+1) by matching each IPO with a control firm that has the similar size and market-to-book ratio. All CARs are winsorized at 1% and 99% level.

		Panel A: $CAR_{i,k}$			Panel B: $\overline{CAR_i}$		
		Mean	Median	N	Mean	Median	N
(1)	Brown and Warner (1985) VW Market-Adjusted	-0.310%	-0.454%	549347	-0.258%	-0.184%	8674
		(0.00)	(0.00)		(0.00)	(0.00)	
(2)	Brown and Warner (1985) EW Market-Adjusted	-0.197%	-0.403%	549347	-0.155%	-0.109%	8674
		(0.00)	(0.00)		(0.00)	(0.00)	
(3)	Long (1990) VW Market-Adjusted	-0.063%	-0.361%	622503	-0.100%	-0.027%	8692
		(0.00)	(0.00)		(0.00)	(0.00)	
(4)	Long (1990) EW Market-Adjusted	-0.192%	-0.464%	622503	-0.210%	-0.140%	8692
		(0.00)	(0.00)		(0.00)	(0.00)	
(5)	Industry and Size Adjusted	-0.127%	-0.096%	618352	-0.164%	-0.095%	8692
		(0.00)	(0.00)		(0.00)	(0.00)	
(6)	Size and Market-to-Book Adjusted	-0.107%	-0.089%	619853	-0.143%	-0.070%	8692
		(0.00)	(0.00)		(0.00)	(0.00)	

Table 2.3

Newly Public Incumbents' Reactions to Withdrawn Industry Peers

This table reports newly public incumbents' reactions to withdrawn peers' IPO filings and withdrawals. Row (1) and (2) reports newly public incumbents' CAR(-1,+1) on withdrawn IPOs' filing dates and withdrawn dates, respectively. CAR(-1,+1) is estimated by using Brown and Warner's (1985) methodology, which the benchmarks are CRSP VW market returns. For each peer's IPO filing, market beta is estimated using daily returns between (-365, -30) and we require that there are at least 30 non-missing observations in the estimation period. All CARs are winsorized at 1% and 99% level.

		$CAR_{i,k}$		
		Mean	Median	N
(1)	Withdrawn Industry Peers' IPO Filing Dates	-0.623%	-0.626%	118534
		(0.00)	(0.00)	
(2)	Withdrawn Industry Peers' IPO Withdrawn Dates	0.032%	-0.301%	116064
		(0.27)	(0.00)	

Table 2.4

Aggregated NPIs' Reactions to Industry Peers' IPO Filings

This table reports aggregated newly public incumbents' reactions to peers' IPO filings. For each IPO, aggregated CAR(-1,+1) is the sum of CAR(-1,+1) of all its industry peers' IPO filing announcements within 3 years following its IPO. Row (1) and (2) report the aggregated CAR(-1,+1) using Brown and Warner's (1985) methodology, which the benchmarks are CRSP VW and EW market returns. Row (3) and (4) show the aggregated CAR(-1, +1) using Long's (1990) numeraire portfolio approach and the benchmark returns are CRSP VW and EW market returns, respectively. Row (5) reports the aggregated CAR(-1,+1) by size and industry matches. Row (6) reports the CAR(-1,+1) by size and market-to-book matches. All CARs are winsorized at 1% and 99% level.

		Aggregated $CAR_{i,k}$		
		Mean	Median	N
(1)	Brown and Warner (1985) VW Market Adjusted	-19.651%	-5.039%	8674
		(0.00)	(0.00)	
(2)	Brown and Warner (1985) EW Market Adjusted	-12.496%	-2.924%	8674
		(0.00)	(0.00)	
(3)	Long (1990) VW Market Adjusted	-4.502%	-0.755%	8692
		(0.00)	(0.00)	
(4)	Long (1990) EW Market Adjusted	-13.786%	-4.640%	8692
		(0.00)	(0.00)	
(5)	Industry and Size Adjusted	-9.015%	-2.743%	8692
		(0.00)	(0.00)	
(6)	Size and Market-to-Book Adjusted	-7.639%	-2.203%	8692
		(0.00)	(0.00)	

Table 2.5

The Determinants of NPIs' Stock Reaction to Industry Peers IPO Filings

This table describes the determinants of NPIs' stock reactions to industry peer IPO filings. The dependent variable, CAR(-1,+1), is estimated by the market model following Brown and Warner (1985) and is multiplied by 100 to ease interpretation. $Ln(Sales)_0$, MB $Ratio_0$, and $Leverage_0$ are NPIs' initial size, market-to-book ratio, and leverage after going public. Listing days are the number of days between NPIs' IPO dates and industry peers' IPO filing dates. Founding age is the NPIs' age at the time of IPOs. VC is a dummy variable that equals one for VC-backed NPIs. Post is a dummy variable that equals one if the NPI goes public after the year 1998. $\Delta Ln(Sales)_t$, ΔMB $Ratio_t$, and $\Delta Leverage_t$ are estimated by the change in Ln(Sales), MB Ratio, and Leverage from time 0 to t, where t is the most recent quarter prior to each industry peer IPO filing. D(Industry Downturn) is a dummy that equals one if the prior month's market-adjusted industry returns are below the median of prior year's market-adjusted industry returns. D(Competitive Industry) is a dummy variable that equals one if an industry's Herfindahl-Hirschman index is within the bottom tercile in a year. Variables are winsorized at 1% and 99%. Standard errors that are clustered by NPIs and p-values are reported in parentheses.

	$CAR_{i,k} \times 100$			
VARIABLES	(1)	(2)	(3)	(4)
$Ln(Sales)_0$	0.043	0.006		
	(0.00)	(0.68)		
MB $Ratio_0$	-0.025	-0.085		
	(0.00)	(0.00)		
$Leverage_0$	0.058	0.032		
	(0.48)	(0.73)		
Ln(Listing Age)	0.122	0.104	0.093	0.077
	(0.00)	(0.00)	(0.35)	(0.42)
Founding Age	-0.001	-0.001		
	(0.48)	(0.56)		
% of Primary Shares Offered	-0.004	-0.002		
	(0.00)	(0.03)		
Underwriter Ranking	-0.014	-0.003		
	(0.14)	(0.74)		
Ln(Primary Share Amount)	0.149	0.112		
	(0.00)	(0.03)		
VC-Backed	0.000	0.014		
	(1.00)	(0.71)		
Post	-0.007	0.121		
	(0.94)	(0.28)		
VC-Backed*Post	-0.249	-0.213		
	(0.02)	(0.06)		
$\Delta Ln(Sales)_t$		-0.141	-0.384	-0.353
		(0.00)	(0.00)	(0.00)
ΔMB $Ratio_t$		-0.175	-0.340	-0.343
		(0.00)	(0.00)	(0.00)

Table 2.5 continues on the next page

Table 2.5 continues from the previous page

ΔLeverage$_t$		-0.209	0.043	0.047
		(0.22)	(0.87)	(0.85)
D(Industry Downturn)				-0.133
				(0.00)
D(Competitive Industry)				-0.326
				(0.00)
Constant	-0.363	-0.163	-0.742	-0.349
	(0.11)	(0.51)	(0.22)	(0.56)
Observations	422,784	422,784	422,690	423,062
R-squared	0.090	0.093	0.111	0.044
Industry-by-Month FE	Yes	Yes	Yes	No
Month FE	No	No	No	Yes
NPIs FE	No	No	Yes	Yes
Peer IPOs FE	Yes	Yes	Yes	No
Cluster by	NPIs	NPIs	NPIs	NPIs

Table 2.6

Industry Peer IPO Effects and 3-year NPIs' Long-run Underperformance

This table reports the 3-year IPO long-run underperformance before and after excluding completed and withdrawn industry peers' IPO filings' impact. Panel A describes the full sample from 1983-2015. Following Barber and Lyon (1997), each IPO is matched with a control firm that has the similar firm size and market-to-book ratio. Firm size is measured as the share prices multiplied by the number of shares outstanding at the end of the IPO month. Book value of equity numbers is the post-issue book value of equity on SDC. If it is missing, we replace it with the book value of equity reported on the nearest quarter after IPOs or the reported pre-IPO equity book values plus the amount of the proceeds. Control firms are firms that have been listed on the stock market for at least five years and did not go SEOs in the past five years. To mitigate the influence from delisting issues, follow Loughran and Jitter (1995), we require that, if an IPO firm delists before its anniversary date, its delisting return is added into its returns and truncate its total return on that date. If a control firm delists, then its delisting return is added into its returns and we replace it with the next closest market-to-book control firm on the next day of the listing date. Similarly, if the second control firm delists, we replace it with a third one. Next, we accumulate the three-year returns for each IPO and its control firm. Then the cumulative return differences between the IPO firm and the control firm are the BHARs, which is measured equally-weighted. To exclude the industry peer pressure, on dates that have an industry peer filing an IPO, we set the (-1, +1) window IPO returns equal to the control firm returns so that the abnormal return for (-1, +1) window is equal to 0. Lastly, we re-accumulate each IPOs' stock returns over three years and refer to the recalculated BHARs as the IPO long-run underperformance after excluding industry peer pressure. In Panel B and C, the newly public incumbents' sample is split by revenues, which is a combination of pre-IPO sales on SDC, post-IPO sales on SDC and sales data at the end of the first fiscal year after IPOs. Sales numbers have been converted into dollars of 2016 purchasing power using the CPI. Panel D reports the results of NPI with missing values in sales.

		BHARs		**Excl. Peer IPO Effects**		**Test for Difference**		
	N	Mean	Median	Mean	Median	Diff (Mean)	P-value (Mean)	P-value (Median)
Panel A: Full Sample								
Full sample	8863	-9.364%	-20.446%	-3.707%	-13.110%	-5.656%	(0.00)	(0.00)
Panel B: Sort into 2 Groups by Sales (in 2016$)								
0-99.999mm	5100	-18.890%	-28.957%	-7.825%	-17.687%	-11.065%	(0.00)	(0.00)
100mm and up	3454	5.545%	-6.935%	3.298%	-5.332%	2.246%	(0.18)	(0.45)
Panel C: Sort into 6 Groups by Sales (in 2016$)								
0-9.999mm	1626	-33.085%	-40.193%	-16.504%	-24.774%	-16.581%	(0.00)	(0.00)
10-19.999mm	650	-28.826%	-33.050%	-17.364%	-23.584%	-11.461%	(0.01)	(0.00)
20-49.999mm	1413	-12.079%	-26.195%	-2.642%	-13.277%	-9.437%	(0.17)	(0.00)
50-99.999mm	1411	-4.777%	-15.419%	1.380%	-10.157%	-6.156%	(0.49)	(0.01)
100-499.999mm	2366	7.127%	-9.666%	3.686%	-6.598%	3.441%	(0.13)	(0.19)
500mm and up	1088	2.103%	-3.091%	2.455%	-4.004%	-0.352%	(0.87)	(0.48)
Panel D: Missing Values in Sales								
Missing sales	309	-18.777%	-27.360%	-14.052%	-16.152%	-4.725%	(0.54)	(0.24)

Table 2.7

Industry Peer IPO Effects and 5-year NPIs' Long-run Underperformance

This table reports the 5-year IPO long-run underperformance before and after excluding completed and withdrawn industry peers' IPO filings' impact. Panel A describes the full sample from 1983-2015. Following Barber and Lyon (1997), each IPO is matched with a control firm that has the similar firm size and market-to-book ratio. Firm size is measured as the share prices multiplied by the number of shares outstanding at the end of the IPO month. Book value of equity numbers is the post-issue book value of equity on SDC. If it is missing, we replace it with the book value of equity reported on the nearest quarter after IPOs or the reported pre-IPO equity book values plus the amount of the proceeds. Control firms are firms that have been listed on the stock market for at least five years and did not go SEOs in the past five years. To mitigate the influence from delisting issues, follow Loughran and Jitter (1995), we require that, if an IPO firm delists before its anniversary date, its delisting return is added into its returns and truncate its total return on that date. If a control firm delists, then its delisting return is added into its returns and we replace it with the next closest market-to-book control firm on the next day of the listing date. Similarly, if the second control firm delists, we replace it with a third one. Next, we accumulate the five-year returns for each IPO and its control firm. Then the cumulative return differences between the IPO firm and the control firm are the BHARs, which is measured equally-weighted. To exclude the industry peer pressure, on dates that have an industry peer filing an IPO, we set the (-1, +1) window IPO returns equal to the control firm returns so that the abnormal return for (-1, +1) window is equal to 0. Lastly, we re-accumulate each IPOs' stock returns over five years and refer to the recalculated BHARs as the IPO long-run underperformance after excluding industry peer pressure. In Panel B and C, the newly public incumbents' sample is split by revenues, which is a combination of pre-IPO sales on SDC, post-IPO sales on SDC and sales data at the end of the first fiscal year after IPOs. Sales numbers have been converted into dollars of 2016 purchasing power using the CPI. Panel D reports the results of NPI with missing values in sales.

		BHARs		**Excl. Peer IPO Effects**		**Test for Difference**		
	N	Mean	Median	Mean	Median	Diff (Mean)	P-value (Mean)	P-value (Median)
Panel A: Full Sample								
Full sample	8863	-17.503%	-24.205%	-3.233%	-15.509%	-14.270%	(0.00)	(0.00)
Panel B: Sort into 2 Groups by Sales (in 2016$)								
0-99.999mm	5100	-25.591%	-31.349%	-3.539%	-19.082%	-22.053%	(0.00)	(0.00)
100mm and up	3454	-3.839%	-10.688%	-0.885%	-8.644%	-2.954%	(0.25)	(0.44)
Panel C: Sort into 6 Groups by Sales (in 2016$)								
0-9.999mm	1626	-51.149%	-44.083%	-16.082%	-31.048%	-35.067%	(0.00)	(0.00)
10-19.999mm	650	-48.766%	-36.580%	-26.699%	-24.046%	-22.067%	(0.01)	(0.00)
20-49.999mm	1413	-6.081%	-22.912%	16.749%	-9.427%	-22.830%	(0.01)	(0.00)
50-99.999mm	1411	-5.002%	-18.876%	1.268%	-10.121%	-6.270%	(0.59)	(0.01)
100-499.999mm	2366	-5.735%	-14.223%	-1.419%	-10.527%	-4.316%	(0.22)	(0.29)
500mm and up	1088	0.284%	-5.374%	0.275%	-5.824%	0.009%	(1.00)	(0.82)
Panel D: Missing Values in Sales								
Missing sales	309	-36.727%	-29.813%	-24.421%	-16.618%	-12.307%	(0.11)	(0.06)

Table 2.8
Industry Peer IPO Effects and 3-year NPIs' Long-run Underperformance in CTP

This table reports the estimates of 3-year IPO long-run stock underperformance using calendar-time portfolio approach. Panel A replicates the results by using cumulative monthly returns from daily returns. Panel B, Panel C, and Panel D show the results after excluding industry peer IPO effects by CRSP value-weighted market returns, control firm returns using size-industry matches, and control firm returns using size-market-to-book-ratio matches, respectively. Specifically, to exclude the industry peer IPO impact, on dates that have an industry peer filing an IPO, we set the (-1, +1) window IPO returns to the VW market returns or the control firm returns. The base model is $R_{pt} - R_{ft} = \alpha + \beta_t (R_{mt} - R_{ft}) + s_t SML_t + h_t HML_t + I_t INVT_t$, where R_{pt} = the monthly return on an equally-weighted calendar-time portfolio; R_{ft} = the monthly on the 3-month T-bill; α = the intercept, the mean monthly abnormal return on the calendar time portfolio; R_{mt} = the monthly return on the value-weighted market index; SMB = the difference, each month, between the returns of a value-weighted portfolio of small and big stocks; and HML = the difference, each month, between the returns of a value-weighted portfolio of high and low book-to-market stocks. INVT = the difference, each month between the returns of a value-weighted portfolio of high and low investment activities stocks. We further restrict that each portfolio should contain at least 10 observations to estimate the regression parameters. When generating the purged SMB HML and INVT, following Ritter and Loughran (2000), we purged out firms that went IPOs or SEOs in the past five years. Moreover, the portfolio is weighted by the number of issuers during each event period.

	Purged Fama-French Three Factors			*Purged Fama-French Three Factors and Investment Factor*		
Variable	Estimate	t-stat	p-value	Estimate	t-stat	p-value
Panel A: 3-year Stock performance						
α	-0.420	-2.310	(0.02)	-0.335	-1.810	(0.07)
MRKRF	1.199	27.580	(0.00)	1.193	27.510	(0.00)
Purged SMB	0.964	15.710	(0.00)	0.948	15.390	(0.00)
Purged HML	-0.423	-5.970	(0.00)	-0.380	-5.200	(0.00)
Purged INVT				-0.260	-2.170	(0.03)
Panel B: After Excl. Industry Peer IPO Effects by CRSP VW Market Returns						
α	-0.297	-1.710	(0.09)	-0.231	-1.310	(0.19)
MRKRF	1.190	28.710	(0.00)	1.185	28.610	(0.00)
Purged SMB	0.677	11.570	(0.00)	0.664	11.300	(0.00)
Purged HML	-0.133	-1.970	(0.05)	-0.100	-1.430	(0.15)
Purged INVT				-0.202	-1.760	(0.08)
Panel C: After Excl. Industry Peer IPO Effects by Size-Industry Match Firm Returns						
α	-0.176	-1.00	(0.32)	-0.095	-0.530	(0.60)
MRKRF	1.151	27.410	(0.00)	1.145	27.330	(0.00)
Purged SMB	0.928	15.670	(0.00)	0.912	15.350	(0.00)
Purged HML	-0.183	-2.680	(0.01)	-0.143	-2.020	(0.04)
Purged INVT				-0.248	-2.150	(0.03)
Panel D: After Excl. Industry Peer IPO Effects by Size-MtoB Match Firm Returns						
α	-0.268	-1.480	(0.14)	-0.189	-1.030	(0.31)
MRKRF	1.161	26.850	(0.00)	1.156	26.770	(0.00)
Purged SMB	0.891	14.590	(0.00)	0.876	14.290	(0.00)
Purged HML	-0.131	-1.850	(0.06)	-0.090	-1.240	(0.22)
Purged INVT				-0.245	-2.050	(0.04)

Appendix 2.A1: Industry Distributions and Characteristics

Table A1 describes the industry distributions and classifications. It shows that there are significant variations across industries. On average, Industry 34 (Business Services) accounts for the largest proportion of IPOs (19.05%) and the largest number of industry peers' IPO filings. However, the number of IPOs in Industry 5 (Tobacco Products), 26 (Defense), and 27 (Precious Metals) is lower than 10. IPOs in Industry 28 (Non-Metallic and Industrial metal mining) and 31 (Utility) tend to have large firm size. IPOs in Industry 5 (Tobacco Products), 16 (Textiles), and 39 (Shipping Containers) tend to go public when they are mature. The IPO first-day underpricing phenomenon are more pronounced in 22 (Electrical Equipment), 34 (Business Services), 35 (Computers), and 36 (Electronic Equipment), which is consistent with the information asymmetry explanation that IPOs with higher information asymmetry tend to underprice more to attract investors to disclose private information. Additionally, IPOs in Industry 12 (Medical Equipment), 13 (Pharmaceutical Products), 34 (Business Services), 35 (Computers), and 36 (Electronic Equipment) are more likely to be backed by venture capitalists.

Table 2.A1
Industry Distributions and Characteristics

This Table describes the industry characteristics of the IPO sample by Fama-French 48 industries. MV is the average market capitalization. Age is the number of years since the founding year. Prcds is the total IPO proceeds in millions. Underpricing is the average IPO underpricing. % # of Comp Peers and # of WD peers represent the number of completed and withdrawn industry peers' IPO filings within 3 years after the incumbents' IPOs. If there are more than one industry peers' filings on the same day, we only keep one of them. Moreover, if a completed and a withdrawn IPO filed the IPO on the same day, we keep the completed IPO's filing. All variables except # of completed peers and # of withdrawn peers are winsorized at 1% and 99% level.

Ind #	Industry Name	N	MV	TobinQ	Age	Prcds	% of Primary Shares	Under pricing	VC	Sales	UW Rank	# of Comp peers	# of WD peers
1	Agriculture	22	268.65	2.66	25.45	111.40	95.51	2.81%	0.14	424.18	6.45	2.05	0.36
2	Food Products	85	361.25	2.60	29.46	88.94	90.73	13.33%	0.14	426.28	6.77	9.99	3.14
3	Candy & Soda	12	505.48	2.46	34.00	177.45	86.17	18.10%	0.08	586.65	5.93	1.33	2.50
4	Beer & Liquor	20	152.34	2.11	28.74	40.47	88.26	11.33%	0.30	95.55	6.55	3.90	0.35
5	Tobacco Products	4	154.84	3.07	57.25	84.70	100.00	14.53%	0.00	271.49	8.75	0.75	0.00
6	Recreation	87	115.48	2.71	14.24	31.74	87.62	16.19%	0.16	106.96	5.70	15.48	4.09
7	Entertainment	158	274.43	2.72	12.99	72.38	91.97	16.07%	0.12	228.52	5.98	24.08	6.84
8	Printing and Publishing	54	390.69	2.65	33.65	82.55	90.00	12.70%	0.13	292.65	6.75	7.50	1.72
9	Consumer Goods	121	220.19	2.88	24.07	58.57	81.12	13.40%	0.11	211.90	6.64	15.91	2.36
10	Apparel	98	280.00	3.00	20.22	66.36	84.22	16.38%	0.09	190.75	7.02	14.41	3.94
11	Healthcare	262	182.98	2.56	8.13	43.10	93.29	11.05%	0.36	152.28	6.89	32.56	10.22
12	Medical Equipment	345	176.25	3.56	9.12	38.19	93.71	13.70%	0.62	36.76	6.67	35.56	9.71
13	Pharmaceutical Products	612	246.60	3.85	8.12	50.59	98.55	12.02%	0.77	27.46	7.20	59.75	16.88
14	Chemicals	90	529.59	2.68	22.53	128.76	90.53	12.26%	0.24	590.40	7.45	10.04	3.20
15	Rubber and Plastic Products	61	119.90	2.16	20.95	38.71	84.21	9.26%	0.13	245.61	6.58	8.36	1.23
16	Textiles	34	164.25	2.07	39.68	57.86	85.94	3.49%	0.09	312.44	7.80	4.62	1.79
17	Construction Materials	80	155.21	2.05	30.55	47.65	86.81	6.08%	0.09	183.14	7.06	11.93	3.73
18	Construction	103	226.77	2.03	20.61	54.63	92.07	9.32%	0.08	249.34	6.88	11.22	3.52
19	Steel Works Etc	67	339.67	1.81	36.01	89.85	83.84	4.21%	0.04	609.90	8.03	10.87	3.21
20	Fabricated Products	17	451.90	2.89	32.53	95.98	96.14	16.65%	0.00	408.36	6.69	2.41	0.71
21	Machinery	191	236.36	2.72	25.21	54.54	88.08	12.15%	0.20	240.94	6.80	28.32	3.69
22	Electrical Equipment	104	322.31	3.39	15.97	50.54	91.60	23.90%	0.32	142.73	6.64	11.78	2.82

23	Automobiles and Trucks	73	414.11	2.08	28.21	92.06	85.72	8.47%	0.07	556.49	7.28	11.86	2.77
24	Aircraft	19	506.87	1.97	28.50	175.72	76.48	6.49%	0.16	488.43	7.58	1.58	0.74
25	Shipbuilding, Railroad Equipment	17	206.84	2.03	31.29	67.52	93.30	8.44%	0.06	327.18	7.75	2.18	0.29
26	Defense	5	74.34	2.22	16.80	22.78	85.23	4.31%	0.40	47.79	7.44	0.80	0.40
27	Precious Metals	9	557.49	4.86	4.67	64.29	98.77	-0.49%	0.00	102.50	8.80	1.44	0.22
28	Non-Metallic and Industrial Metal Mining	10	906.11	2.98	18.50	223.86	97.28	7.64%	0.10	576.81	8.93	0.50	1.80
29	Coal	10	640.74	1.42	12.56	264.78	94.78	2.19%	0.00	895.96	8.61	0.60	0.50
30	Petroleum and Natural Gas	176	732.36	1.97	18.25	175.55	92.15	5.95%	0.14	415.59	8.09	18.04	9.43
31	Utilities	40	992.02	1.60	19.16	283.88	96.44	7.24%	0.10	978.71	8.26	3.75	2.83
32	Communication	314	516.75	2.76	9.78	121.87	93.57	19.09%	0.37	180.64	7.83	39.94	23.10
33	Personal Services	128	292.62	3.32	17.47	63.25	87.53	18.75%	0.23	204.09	7.09	17.11	4.41
34	Business Services	1688	441.39	4.63	10.10	64.19	88.57	31.77%	0.53	116.01	7.40	164.82	45.99
35	Computers	510	396.26	4.23	8.72	49.34	89.24	24.64%	0.57	100.34	7.00	59.14	8.44
36	Electronic Equipment	491	453.12	3.71	11.47	65.33	88.80	26.52%	0.54	162.08	7.34	53.81	11.38
37	Measuring and Control Equipment	158	271.21	3.14	13.79	43.13	87.97	17.63%	0.43	85.38	6.84	19.16	3.38
38	Business Supplies	41	292.09	2.03	28.84	81.38	81.73	6.08%	0.15	556.90	7.48	7.02	1.78
39	Shipping Containers	24	359.85	1.98	46.67	115.55	71.12	2.99%	0.08	626.83	7.90	2.75	0.33
40	Transportation	223	311.13	2.08	17.95	104.07	90.20	9.09%	0.08	340.82	7.52	23.39	5.62
41	Wholesale	366	183.21	2.42	17.71	52.70	90.95	10.91%	0.15	405.33	6.29	47.43	12.78
42	Retail	527	267.95	2.64	22.28	59.34	85.48	14.59%	0.24	392.83	7.42	59.46	14.67
43	Restaurants, Hotels, Motels	210	316.86	2.68	14.73	73.00	89.76	17.58%	0.13	220.22	6.80	24.07	6.08
44	Banking	416	315.98	1.29	30.65	80.59	92.86	9.81%	0.08	245.51	7.34	24.25	8.35
45	Insurance	259	531.55	1.87	19.44	140.59	86.90	10.32%	0.10	591.81	7.78	29.41	5.54
46	Real Estate	49	379.74	2.04	20.12	88.91	90.51	9.66%	0.12	364.56	7.65	5.47	2.29
47	Trading	358	396.05	2.16	23.53	104.21	91.22	9.40%	0.09	248.09	7.37	35.24	12.96
48	Other	115	189.56	2.51	10.79	50.26	90.80	10.91%	0.20	74.33	6.53	0.00	0.00

Appendix 2.A2: Fitbit's Example of Excluding the Industry-Follower IPO Effects

This figure plots the 3-year stock prices of Fitbit. The red asterisks depict the days that Fitbit's industry peers file IPOs. To exclude the stock reactions to peer IPO activities, whenever an industry peer files an IPO, we set the 3-day returns of an NPI equal to the market returns or control firms' returns. The underlying assumption is that if nothing happens, the incumbents' stock returns should on average converge to the benchmark returns.

Chapter 3 : Why are Some SEOs not Withdrawn?

Abstract

Most firms that experience large negative market-adjusted returns over the filing periods of their seasoned equity offerings (SEOs) complete rather than withdraw their SEOs. We examine the factors that affect the issuance decision and find that it is not related to insufficient corrections to overvaluation. Firms rely more on industry and market-level information than they do on idiosyncratic information when making the issue/withdraw decision. We argue that issuing helps firms meet exchange listing rules and our results indicate that the issuance decision is a defence against delisting. Finally, we find that issuing firms' decisions to complete their SEOs are more value enhancing than had they made the decision to withdraw.

Keywords: Seasoned Equity Offering, Raising capital, Long-run performance

JEL Classifications: G30, G32, G82

3.1 Introduction

A common explanation for withdrawn seasoned equity offerings (SEOs) is that managers avoid issuing securities that they view as underpriced. Economically significant negative filing period returns reported in Mikkelson and Partch (1988) and Clark, Dunbar, and Kahle (2001) support this view. Our examination of 224 withdrawn issues over the period 1983-2016 yields similar results. We find that the average stock return between the filing and withdrawal date is -24%. Interestingly, over the same period, we observe that a substantial number of firms experience similar extremely negative filing period returns and complete their SEOs. For instance, in our sample of 4,886 SEOs, 635 filing firms have market-adjusted filing period returns of -20% or lower. Of these, only 121 filers withdrew. The remaining 81% completed their SEOs. In this paper, we investigate possible explanations for why these similar extremely negative filing-period returns elicit different issuance decisions. Looking at the dual of the issuance decision, we document that the decision to withdraw is not driven by stock returns alone.[43]

Clarke, Dunbar, and Kahle (2001) also examine the decision to withdraw. They compare all cancelled SEOs to all completed SEOs. In this paper we compare firms that withdraw SEOs to firms that complete their offerings despite experiencing economically significant negative filing period returns. Specifically, after calculating the filing period returns of all firms that complete their SEOs, we categorize the 931 firms in the bottom quintile of filing period market-adjusted return distribution as sharp-drop (SD) SEOs.[44] SD SEOs experience average returns of -23% over the period from filing to SEO completion. We compare the SD firms to the firms that withdrew their offerings. Figure 3.1, Panel A

[43] Our findings are consistent with Alti and Sulaeman (2012) who report that equity issuances are not driven solely by stock returns.

[44] Our results are robust to selecting firms in the bottom quintile of raw (unadjusted) filing period returns.

shows that the average post-filing market-adjusted returns of the sharp-drop sample is very similar to that of the firms that withdrew.

Perhaps the simplest explanation for the different issuance decisions comes form the hypothesis that managers choose to issue equity when it is overvalued. Under this explanation, overvaluation leads both withdrawing and SD firms to file. For a firm that eventually withdraws, the sharp price decline is sufficient to push the market price to or below management's assessment of the firm's intrinsic value. For a sharp-drop firm, the negative filing period returns do not remove all of the overvaluation, so management proceeds with the issuance. This behaviour is analogous to the decisions to complete share repurchases documented in Ikenberry, Lakonishok, and Vermaelen (2000). In this scenario, we would expect to observe no further negative returns following withdrawals and further negative returns following sharp-drop issuances. Figure 3.2 shows, the long-run returns following withdrawn offers and sharp-drop SEO completions are similarly negative. In formal tests we find that there is no significant difference in long-run returns in the three years following the decision to withdraw or to issue following a sharp drop in stock prices. Our finding of negative long-run excess returns following withdrawals is consistent with that in Anderson and Betker (2000) and contradicts that reported in Clark et al. (2001).

We next turn to firm and issuance level attributes as possible determinants of the different issuance decisions. We begin with a closer look at the filing period returns. Existing research, and this paper shows that negative stock returns precede SEO withdrawal. Mikkelson and Partch, (1988) and Atinkilic and Hansen (2003) refer to these negative returns as being due to unfavorable "market conditions." Papers examining the withdrawal of IPOs also highlight the importance of market conditions. However, the lack of market prices for pre-IPO firms restricts such work to documenting an inverse relation between IPO withdrawal and returns on the entire market during the filing-period (e.g. Bernstein, 2015). Our setting allows us to examine the importance of market-wide, industry-level, and idiosyncratic returns in the decision to issue or withdraw.

Given our sample construction method, the similarity in the raw filing period returns of the withdrawn and SD samples is not surprising. What is interesting is the differences in composition of those returns. First, the industry conditions facing SD and withdrawing firms differ significantly. The average filing period industry return for the SD sample is not different from zero while the average filing period industry return for the withdrawn sample is a statistically significant -3.40%. Second, there is no significant difference in the filing period market returns (net of own industry returns) between SD and withdrawing firms. Finally, firm returns adjusted for both market and industry returns do not differ between SD and withdrawing firms. These results suggest that even in the presence of firm specific information, industry level information is an important determinant of the decision to issue equity. Later results from linear probability models confirm this.

We next look at how the SD firms could benefit from their equity issuances. DeAngelo, DeAngelo, and Stulz (2010) document that the dominant reason for the unconditional probability of SEO issuances is issuers' short-term liquidity problem. It is possible that SD firms face more severe short-term liquidity problems than do withdrawing firms. Consistent with DeAngelo, DeAngelo, and Stulz (2010), we find a positive relation between a firms' ex-post cash needs and their decisions to complete rather than withdraw SEOs in the face of extremely negative filing-period returns.

Publicly traded firms need to meet certain price and capitalization thresholds to maintain their exchange listings. Extremely negative filing period return can push firms closer to these listing thresholds. If listings are valuable, firms may issue to increase capitalization. Increasing shares outstanding also increases ability to conduct reverse splits.

We find that, relative to the withdrawing sample, the SD firms are closer to market capitalization delisting thresholds, have higher predicted likelihoods of delisting. These are consistent with SD firms issuing to maintain their listings.

Lee and Masulis (2009) suggest that underwriters have more say than issuers in the withdrawal decision. This leads us to look at whether the quality of the underwriter affects the decision to issue in the face of negative filing period returns. Unconditionally, firms with high quality underwriters are more likely to withdraw. However, when we look at the interaction of underwriter quality and firm specific information, things change as firms with low ranked underwriters are more likely to withdraw. This is because idiosyncratic stock returns significantly affect the issuance decision for firms with high quality underwriters. For such firms, there is a positive relation between issuance and idiosyncratic returns. We also note that although high quality underwriters do pay attention to idiosyncratic information, they place significantly more weight on industry level information.

We provide additional evidence on the relation between delisting concerns and SD issuance. Relative to firms that withdraw, SD firms are less likely to delist in the two-year period following the decision to withdraw/issue. The survival benefits of issuing disappear after the second year. Issuing in the face of sharp drops protects listing status in the short term. We also provide evidence that SD firms are more likely to engage in reverse splits following their issuance. This is consistent with these firms defending their listing status.

Finally, we examine the market reaction to the decisions to withdraw or issue following significantly negative filing period returns. Unconditionally, the market adjusted return at the time SD firms decide to issue is significantly more negative (-1.52%) than the market adjusted return at the time of withdrawn offers (-0.08%). However, estimation of an endogenous switching model shows that issuing firms would have incurred a significantly more negative market reaction had they decided to withdraw. We also show that withdrawing firms would have suffered larger abnormal returns had they decided to issue. These results are consistent with both SD and withdrawing firms making optimal issuing decisions in the face of negative filing period returns.

Overall, this paper makes the following contributions. First, we show that withdrawal decisions are not the result of negative filing period returns reducing mispricing. Second, we show that for a large fraction of issuing firms, idiosyncratic information does not affect the issuance decisions and that industry-wide information is an important input in the decision to complete SEOs. Further, for firms with high quality underwriters, even though idiosyncratic information influences the issuance decision, its weight in the decision is only about one third of that of industry wide information. We also present novel evidence that delisting concerns affect issuance decisions. This finding suggests that in some cases the formation of equity capital is a defense against delisting.

3.2 The Decision to Withdraw

Mikkelson and Partch (1988) argue that managers withdraw filed equity offerings when they view the current market price as too low and complete such offerings when they view current market price as being not “too low.” They report negative raw returns and one-factor market model prediction errors on average in the period between filing and withdrawal. They also find that the average raw return (prediction error) in the period between filing and completion is positive (non-negative). Basically, the decision to withdraw prevents issuance of undervalued equity while the decision to proceed results in the issuance of equity whose market price is at or above managers’ assessed value.

This view fits nicely with studies suggesting that market timing or mispricing drive the SEO decision (Loughran and Ritter, 1995; Baker and Wurgler, 2002). It also motivates our first research question which is whether the stock returns following withdrawal are less negative than those following issuance by SD firms. Since this view relies on a divergence between the market price and managers' assessment of the value of the firm's equity, we would also expect that the decision to withdraw is heavily influenced by firm specific information as opposed to market wide or industry information.

An alternative explanation for firms to issue shares following economically significant negative filing period returns is survival. Relative to firms that withdraw SD firms may face more urgent cash needs or be closer to financial distress (DeAngelo, DeAngelo, and Stulz, 2010; Park, 2015; Walker and Wu, 2019). Correspondingly we examine the effect of firms' cash needs and measures of financial distress on the decision to withdraw or issue after experiencing negative filing period returns.

Absent actual financial distress SD firms may face delisting. For example, to maintain a NSDAQ listing, firms must maintain a minimum level of market capitalization the market value of public float, bid price, and public float (# of shares). The economically significant negative filing period returns make it likely that the firm is closer to the minimum listing requirements. Remaining publicly listed eases firms' acquisitions of other targets (Maksimovic, Phillips and Yang, 2013), helps them raise future capital in a more timely manner (Brav, 2009), and facilitates their engagement in potential investment opportunities (Gilje and Taillard, 2016). In addition to losing those benefits delisting is costly. For example, Bakke, Jens, and Whited (2012) document that delisted firms experience cuts in investment, cash savings, and employment and Macey, O'Hara, and Pompilio (2008) find that the percentage spreads are tripled, and volatility is doubled.

Completing an SEO boosts market capitalization, the value of public float, and the number of shares outstanding. The last of those helps maintain a minimum bid price by facilitating reverse splits. The benefits of remaining listed potentially motivate SD firms to issue in the face of negative filing period returns. We examine the importance of delisting concerns by including variables that capture variation on firms' distance to delisting in our analysis of decisions to complete offerings following negative filing period returns.

3.3 Data

3.3.1 Sample Selection and Variable Definitions

We obtain a sample of SEOs from Thomson Reuters SDC between 1983 and 2016. We start in 1983 because SDC starts providing filing information in 1983. To remain in the sample, an SEO must meet the following criteria: 1) have CRSP and Compustat data; 2) have four-digit SIC codes outside 4900-4999 (utilities) and 6000-6999 (financial firms); 3) have available filing information; 4) have securities with share codes 10 or 11. 5) excluding ADRs, closed-end funds, unit offerings, limited partnerships, and real estate investment trusts); 6) be listed on the NYSE, Nasdaq, or Amex; 7) have stock prices above $1; 8) not be a pure secondary offering,[45] and 9) have positive total assets in Compustat.

Next, we revise the actual SEO issuance dates following the methodologies in the prior studies. Notably, prior studies document that many SEO issue dates on SDC do not adjust for the fact that SEO offerings are launched after the close of daily exchange trading. Following Corwin (2003) and Safieddine and Wilhelm (1996), we apply a volume-based issuance date correction. The rationale is that if there should be large volume surge on SEO issuance dates—specifically if the trading volume on the day following SDC issue date is 1)

[45] We also drop 52 withdrawn SEOs indicating that they are pure secondary share filings.

more than twice the trading volume on SDC issue date and 2) more than twice the average daily trading volume over the previous 250 trading days—then the dates following SDC issue dates are determined as the issue dates.

Most of our analyses below benchmark the SD SEOs on the withdrawn SEOs. Nevertheless, one concern is that the reasons for withdrawals may be more heterogeneous than SEO completions. For example, a firm may withdraw an SEO when it becomes a potential target in an M&A deal. Ideally, we seek to obtain a sample of withdrawn SEOs whose withdrawal decisions are triggered by stock returns instead of by other unrelated reasons such as potential acquisition opportunities.

To make the SD SEO sample comparable to that of withdrawn SEOs, we place the following restrictions for the SEO sample: (1) We keep only non-shelf registrations because the withdrawn SEO sample in SDC does not contain shelf registration withdrawals.[46] (2) We restrict the filing period to less than 90 days for both completed and withdrawn SEOs to keep the filing period clean.[47] (3) We further drop 14 withdrawn SEOs that were acquired within one year after withdrawn dates (using the delisting code on CRSP) and 1 failed bid (manually checked on Edgar). (4) To further establish that SEO withdrawals are not driven by other idiosyncratic reasons, we also manually check withdrawn SEOs that experience positive filing-period returns on Edgar. We find that 3 withdrawn SEOs with filing-period

[46] We confirm this finding with the SDC customer service. We also carefully examine the withdrawn SEOs on Edgar, and find 2 withdrawn shelf-registration offers in the sample (the filing documents indicates they are under Rule 415, which are shelf registrations). We also drop them from the withdrawn sample.

[47] Over 95% of completed non-shelf SEOs and 60% of withdrawn SEOs are completed within 90 days.

returns above 5% indicating on the Form RW that market conditions are the primary reason for withdrawing.[48] In total, we keep 11 withdrawn SEOs with positive filing-period returns.[49]

Overall, applying these selection criteria mitigates the concerns that the reasons for withdrawal decisions may be heterogeneous and guarantees that the SD SEO sample is comparable to the withdrawn SEO sample. After applying these criteria, our final sample consists of 4,886 non-shelf-registration SEOs, of which there are 4,655 completed SEOs and 231 withdrawn SEOs between 1983 and 2016.

3.3.2 Definition of SD SEOs

We identify our sample of SD SEOs using each SEO's filing-period market-adjusted return. We define the filing period as the time period between filing dates and one day before issuance (withdrawn) dates (inclusive) to exclude the impact of SEO underpricing documented in the prior literature (Corwin 2003). We benchmark each SEO's filing-period returns by using the CRSP value-weighted market returns to calculate the market-adjusted returns. Thus, the filing-period market-adjusted stock returns are calculated as follows:

$$FP\ Mkt\text{-}Adj\ Ret_{i,t} = \prod_{t=fdate}^{issdate(wdate)-1} \left(1 + Ret_{i,t}\right) - \prod_{t=fdate}^{issdate(wdate)-1} \left(1 + VW\text{-}Mkt\,Ret_{i,t}\right) \tag{3.1}$$

We split the 4,655 completed SEOs into quintiles by their filing-period market-adjusted returns and refer to firms in the bottom quintile as SD SEOs. We refer to the remaining four quintiles as Other (completed) SEOs. We plot the filing period returns over

[48] For example, M/I Schottenstein Homes Inc experiences filing-period returns of 11.28%, but its filing-period industry return is -6.08%, which is consistent with the notion that issuers may ignore the idiosyncratic returns while making the withdrawal decisions based on industry-level information.

[49] The rest 8 withdrawn SEOs have filing-period returns below 4%. Dropping the withdrawn SEOs with positive filing-period returns does not materially affect our results.

a fixed event window of (0, 270) calendar days relative to the filing date for SD, Other, and withdrawn SEOs in Figure 3.1A.[50] The filing period returns of our SD sample are statistically indistinguishable from those of firms who withdraw their filings. This suggests that non-market related information is not driving the decision to compete or withdraw.

For each SEO firm, i, we also calculate its filing-period industry returns by using value-weighted Fama-French 49 industry returns:

$$FPIndRet_{i,j,t} = \prod_{t=fdate}^{issdate(wdate)-1} \left(1 + VW\text{-Industry}\, Ret_{i,t}\right) \tag{3.2}$$

We plot the industry filing period returns for SD, Other, and withdrawn SEOs in Figure 3.1B. This graph shows that there are substantial differences in the post filing industry returns of Other, SD, and withdrawn SEOs. For our analysis it is interesting that relative to firms that withdraw, SD firms face more favorable industry conditions. Firms that eventually withdraw are trying to raise capital at a time when their entire industry is losing value. Overall, Figure 3.1B suggests that industry-wide information during filing-period contributes to the SD SEOs' completion decisions.

3.3.3 Cumulative Firm and Market Prediction Errors

Figures 3.1A and 3.1B suggest that firm specific information may not be important and that industry level returns are important in the decision to complete SEOs in the face of negative filing period returns. Those figures do not control for differential exposure to

[50] Using a fixed window of three quarters lets us capture more withdrawing firms. Of firms that file and issue, 99% have issued within 90 days of filing. This same 90 window only captures 60% of firms that file and withdraw. Extending the window to 270 days captures 85% of firms that file and withdraw and all firms that file and issue.

market and industry factors. To address that we calculate firm level prediction errors net of industry and market, market level prediction errors net of industry.

We estimate firms' cumulative prediction errors by using pre-filing returns. Specifically, for each firm i, we estimate the following regression over the period (-250, -20) days prior to the filing dates.

$$r_{ijt} = \alpha + \beta_i \times r_{Mt} + \gamma_i \times r_{jt} + \varepsilon_{ijt} \tag{3.3}$$

Where i, j, and t denote firm i, industry j, and day t. r_{Mt} and r_{jt} denote daily value-weighted CRSP market returns and value-weighted Fama-French 49 industry returns, respectively. We extract the estimates $\hat{\alpha}$, $\hat{\beta}_i$, and $\hat{\gamma}_i$ in the equation above. Over the filing period between filing dates and issue (withdrawn) dates, we calculate each firm i's daily prediction errors as:

$$PE_{ijt}^{firm} = r_{jt} - \left(\hat{\alpha} + \hat{\beta}_i r_{Mt} - \hat{\gamma}_i r_{jt}\right) \tag{3.4}$$

and cumulate the PE_{ijt}^{firm} over the filing period as follows:

$$CumFPE_i = \prod_{t=1}^{compdate-1} (1 + PE_{ijt}^{Firm}) - 1 \tag{3.5}$$

$CumFPE_i$ is an estimate of each firm's idiosyncratic filing period returns.

Furthermore, prior studies in the IPO literature occasionally use industry returns as a proxy for market-wide information (Edelen and Kadlec, 2005). Because the market returns also contain industry j's information, for each industry j, we regress the value-weighted CRSP market returns on the value-weighted Fama-French 49 industry returns over the period (-250, -20) prior to the filing dates. Using the parameters form those models for each industry we estimate a daily market prediction error, $\left(PE_{ijt}^{Mkt} = r_{Mt} - \left(\hat{\lambda} + \hat{\eta}_{j} r_{jt} \right) \right)$. We then cumulate those market prediction errors over each firm's filing period to estimate net of industry market conditions. This variable is called $CumMPE_{i}$.

3.3.4 Distance-to-delisting and Ex-ante Probability of Delisting

To stay listed, a public company must satisfy, *inter alia*, minimum requirements of market capitalization and stock prices. For example, the NYSE states that "A company will be considered to be below compliance if its average global market capitalization over a consecutive 30 trading-day period is less than $50,000,000…". Using a sample of delisting firms on the NYSE and Nasdaq between 1999 and 2004, Macey, O'Hara, and Pompilio (2008) find that failing to meet the minimum requirements of the market capitalizations and stock prices are the primary reasons for delisting.

We use two proxies to measure if an SEO firm is close to delisting. First, we measure the distance-to-delisting as follows:

$$Distance\text{-}to\text{-}Delisting_{i,e,t} = \frac{\overline{MVE_{i,e,t}} - Threshold_{e,t}}{\sqrt{\sigma(MVE_{i,e,t})}} \tag{3.5}$$

Where, i and e denote firm and the stock exchanges where the firm is listed, respectively. One empirical challenge is that the minimum requirements of market capitalization, $Threshold_{e,t}$, is time-varying and is generally unobservable by researchers. Nevertheless, for firms that are listed on the same stock exchange and conduct SEOs during the same time, the minimum requirements of market capitalization, $Threshold_{e,t}$, will be the same. To address this challenge, we include exchange-by-year fixed effects in our empirical tests. Since the market capitalization thresholds are the same for firms on the same exchange at the same point in time, the fixed effects absorb the time and exchange varying thresholds. With the exchange-by-year fixed effects, the distance-to-delisting measure becomes:

$$\textit{Distance-to-Delisting}_{i,e,t} = \frac{\overline{MVE_{i,e,t}}}{\sqrt{\sigma(MVE_{i,e,t})}} \tag{3.6}$$

We estimate the distance-to-delisting measure by using the daily market capitalizations 180 days before SEO filings.[51] We construct a similar distance to delisting measure using stock prices over the 180-day before SEO filings (adjusted for stock splits) because the firms also face delisting thresholds based on stock price.

Second, we complement the distance-to-delisting measure by using an ex-ante delisting probability proxy, $Prob(Delisting)_i$, which is measured as the predicted probability of delisting from the stock exchanges. Specifically, we use all listed firms to estimate a logit model of delisting in quarter *t* based on observable characteristics at time (t-1). Our logit model is similar to that used in Campbell, Hirscher, and Szilagyi (2008).[52] For each of our SEO firms we use the model parameters to estimate an ex-ante probability of delisting in the quarter preceding the quarter preceding a firm's filing.[53]

[51] The results remain the same if we use 270-day pre-filing market capitalizations. Using different windows does not materially affect our results.

[52] There are two differences between our logit regression and that of Campbell et al. (2008). First, their dependent variable is a dummy variable that equals 1 for firms that filed for bankruptcy under Chapter 7 or Chapter 11 (page 2903; however, they also consider a broader failure indicator by including firms that were delisted due to financial reasons and received D ratings). Second, their data is at a monthly frequency and ours is at a quarterly frequency.

[53] Table 3.A1 in the Appendix presents the logit regression estimation.

3.3.5 Summary Statistics

Table 3.1 describes the summary statistics across the full sample, SD, Other, and withdrawn SEOs as well as the two-sample t-tests across subsamples. All variables except non-institutional ownership are winsorized at 1% and 99% level to mitigate the impact of outliers. Non-institutional ownership is winsorized between [0, 1].

First, filing-period market-adjusted abnormal returns are statistically insignificant between SD and withdrawn SEOs. Withdrawn SEOs' filing date CARs(-1,+1) is more negative than SD SEOs' and is marginally significant. Moreover, the cumulative FPE is insignificant between SD and withdrawn SEOs. This evidence is consistent with Figure 3.1 Panel A that SD and withdrawn SEOs experience considerable and similar price declines during the filing period. Moreover, SD SEOs experience better filing-period industry returns than the withdrawn sample (0.12% versus -3.40%). Second, SD SEOs have stronger ex-post cash needs than withdrawn SEOs. Lastly, moving to the delisting measures, SD SEOs are closer to delisting and have lower average stock prices, though they are statistically insignificant before accounting for the stock exchange differences.

Some of the control variables also worth noting. First, as for deal level characteristics, SD SEOs tend to sell a smaller proportion of secondary shares, file a smaller amount on the filing dates than withdrawn SEOs, and hire low-quality underwriters compared to withdrawn SEOs. Second, though statistically insignificant, SD SEOs are smaller than the withdrawn SEOs. Third, SD SEOs tend to hold larger amount of cash, more negative cash flows and are younger compared to other subsamples. Lastly, SD SEOs have significantly less access to the debt market and only 7% of them have credit ratings.

3.4 Results

Our empirical analysis proceeds in four steps. First, we examine the long-term stock performance using the calendar-time portfolio approach. Second, we explore the determinants of completion decisions between SD and withdrawn SEOs. We also show that our results are unlikely to be explained by financial distress measures and further explore underwriters' roles in the completion decisions. Third, we investigate whether SD and withdrawn SEOs differ regarding future delisting and reverse split activities. Finally, using an endogenous switching model, we compare the CARs(-1,+6) on issue (withdrawn) dates for SD and withdrawn SEOs.

3.4.1 Long-term Stock Performance

We use the calendar-time-portfolio approach in Mitchell and Stafford (2000) to examine abnormal returns following withdrawals and issuances by SD and Other firms. For example, we form our portfolio of withdrawal firms in each month t as all firms that withdrew their SEO in the past 36 months. We follow Shumway (1997) and correct for survivorship bias by including delisting returns. We also exclude months with fewer than 5 event firms in its portfolio. We then create an equally weighted portfolio return using the firms in each month's portfolio. We rebalance the portfolios at the end of each month. We follow the same process in creating the returns for the SD and Other portfolios.

We use the portfolio returns to estimate abnormal returns using the time-series regression equation

$$R_{pt} - R_{ft} = \alpha_i + \beta_1\left(R_{mt} - R_{ft}\right) + \beta_2 PSMB_t + \beta_3 PHML_t + \beta_4 PRMW_t + \beta_5 PCMA_t + \varepsilon_{it} \quad (3.7)$$

We estimate three versions of the model. The first only includes the Fama-French three factors, the second adds the investment factor in Lyandres, Sun, and Zhang (2008), and the third includes the Fama-French five factors. Concerns of "factor contamination" lead us to follow Loughran and Ritter (2000) in creating purged factors. Specifically, we recreate each month's asset pricing factors but exclude firms that conducted IPOs or SEOs in the past 60 months.[54] Prior studies show that the power of tests will increase if we weight firms equally instead of weighting each time periods equally (Loughran and Ritter, 2000). Therefore, we follow Spiess and Affleck-Graves (1999) and apply weighted least square (WLS) with weights based on the number of event firms in each monthly portfolio.[55]

Table 3.2 presents the results of this analysis. First, the SD portfolio earns negative and statistically significant returns following SEO issues. For example, SD SEOs, on average, earn -86.16 basis points per month over the 36 months following the SEO completion months, which translates into an annual abnormal return of -9.86%. Columns (2) and (3) show that while the purged investment factor and the purged Fama-French five factors reduce the magnitude of the abnormal performance, there is still evidence of statistically and statistically significant post-issuance underperformance for SD firms (-8.5% and -5.5% negative annual underperformance performance). This supports the idea that SD firms issue because the negative filing period returns did not fully remove any overvaluation that led to filing.

Examination of the estimated alphas for the portfolio of withdrawn also shows evidence of economically and statistically significant post-issuance underperformance. The portfolios of withdrawn SEOs generate monthly alphas between -83 basis points and -68

[54] Loughran and Ritter (2000) do not generate purged market factor since they claim that they are willing to accept the market factor as an equilibrium priced risk factor.

[55] Our results are quantitatively and qualitatively similar is we estimate using OLS.

basis points, and all three alphas are statistically significant.[56] The estimated alphas indicate negative annual underperformance performance ranging from -9.5% to -7.9%. This does not support the idea that the reason for withdrawal is that the negative filing period returns removed pre-filing overvaluation. Lastly, the alphas for the "Other SEOs" portfolios are negative and significant but of smaller magnitude than those of the SD and withdrawn SEOs.

We test whether the estimated alphas differ between groups using portfolios that are (1) long withdrawn SEOs and short SD SEOs, (2) long Other SEOs and short SD SEOs, and (3) long Other and short withdrawn SEOs. We regress the monthly long-short portfolio returns on purged Fama-French three factors, adding the purged investment factor and purged Fama-French five factors. The estimated alphas are presented in Panel B of Table 3.2.

The estimated alphas for the first strategy compare the long-run performance of SD and withdrawn SEOs. The estimates range from 7 to 28 basis points and each is statistically insignificant. These results are inconsistent with the idea that negative filing period returns remove all of the overvaluation of firms that withdraw and leave SD firms somewhat overvalued. As a result, we do not think that differences in overvaluation following negative filing period returns explain the different issuance decisions.

We note that the estimated alphas for the second strategy are 29.9, 35.1, and 28.8 basis points per month and are statistically significant (the alpha in the Fama-French five factors is marginally significant). This evidence is difficult to reconcile with the market timing hypothesis because it would predict that Other SEOs, which are more likely to be

[56] Clarke, Dunbar, and Kahle (2001) measure 3-year buy-and-hold abnormal for a sample of 174 withdrawn SEOs and report statistically insignificant abnormal returns of -3%.

successful market timers than firms experiencing economically significant negative filing period returns.

3.4.2 The SD SEO Completion Decisions

In this section we use the SD sample and firms that withdraw their SEOs and model the SD SEO completion decision using a linear probability model. The dependent variable equals one if an SEO is eventually completed after substantial price declines (SD SEOs) and zero if it is withdrawn. We include the exchange-by-year fixed effects to compare SEOs with the same delisting market capitalization threshold. We further control for industry-by-year fixed effects to remove any time-varying industry-level shocks.

To determine how firm, industry, or market level information affects the decision, we include firm level prediction errors ($CumFPE_i$), industry returns ($FPIndRet_{i,j,t}$). and industry-adjusted market return ($CumMPE_i$) cumulated over each firm's filing period. To examine the role of delisting concerns we include either (i) the distance to delisting measure described in equation (4) and the average share price in the 180-day period prior to filing or (ii) the estimated probability of delisting as estimated using the model in Appendix 1. Additionally, following DeAngelo, DeAngelo, and Stulz (2010) and Huang and Ritter (2018), we include an ex-post cash needs variable that estimates a pro forma cash/total asset after SEOs, assuming that each issuer does not get the proceeds from SEOs.[57]

We follow Lee and Masulis (2009) in our selection of control variables, including both firm-level and deal-level controls including (among others) total assets, the market-to-book ratio, underwriter ranking. We include firm-level accruals to verify that our results

[57] We reverse the pro forma cash level variable so that we can interpret a larger number of this variable as stronger cash needs.

are not driven by the different levels of information asymmetry between SD and withdrawn SEOs. We include listing age to proxy for issuers' life cycles as younger firms are more likely to issue SEOs to finance their investment opportunities (DeAngelo, DeAngelo, and Stulz (2010). Another important consideration is institutional investor demand. Gao and Ritter (2010) and Alti and Sulaeman (2012) find that institutional investors' presence can create short-term demand to facilitate SEOs. We follow Gao and Ritter (2010) and use the non-institutional ownership ratio to proxy for the lack of institutional investor demand. The non-institutional ownership ratio is equal to one for SEOs that are not covered in the 13F database. Lastly, we control for the distance between filing dates and issue (withdrawn) dates to account for the different lengths between SD and withdrawn SEOs filing dates and decision dates.

Table 3.3 presents the results of SD SEOs' completion decisions. In all specifications, the estimated relation between cumulative FPE and the decision to issue is statistically insignificant. This is inconsistent with managers basing the decision on superior knowledge of their firms' value. In contrast, cumulative industry returns have a positive and significant impact on the decision to issue in the face of negative filing period returns. A one-standard-deviation increase in cumulative industry returns is associated with approximately 8.92%-9.57% increases in SD completion probabilities showing the industry returns are both economically and statistically significant. Additionally, the estimated effect of the cumulative Market prediction error (MPE) is positive and significant in all specifications. Recall, that this measure is orthogonal to the industry returns. These results point to the importance of industry and market information on SEO completions even in the presence of idiosyncratic information.

Delisting concerns significantly influence the decision to issue. Firms with greater distance to delisting are less likely to issue in the face of negative filing period returns. We also observe firms with higher share prices are less likely to complete their issuances. This is consistent with our delisting concern explanation because public firms will be forced to delist if their stock prices remain too low for a certain period.[58] Looking at the models columns (4) and (5) show that firms with higher probability of delisting are more likely to complete their SEOs. These results support the idea that some firms issue to maintain their listed status.

One concern is that prior studies also document that the probability of SEOs increases as firms become more financially distressed (DeAngelo, DeAngelo, and Stulz, 2010; Park 2017). It is possible that our measures of delisting likelihood are simply picking up distress. We address this by re-estimating the models in columns (3) and (5) of Table 3.3 with the addition of Altman's Z-Score and Ohlson's O-score, two measures that predict financial distress. The results are presented in Table 3.4. Models (1) and (2) use the z-score and models (3) and (4) use the O-score. The results show that the distress measures do not significantly affect the likelihood of issuing in the face of negative filing returns. Further, the inclusion of the distress variables does not change the economic or statistical significance of the variables related to delisting. We recognize that distress/bankruptcy can cause delisting but note that Macey, O'Hara, and Pompilio (2008) report that failing to maintain the minimum requirements of market capitalizations and stock prices dominate bankruptcy as the reason firms delist from the NYSE and NASDAQ.

Table 3.3 also shows that firms with higher quality underwrites are more likely to withdraw in the face of negative filing period returns. This is consistent with a result shown in Lee and Masulis (2009). Motivated by the prior studies suggesting that underwriters play

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[58] For example, the NYSE requires that "if a security's price closed below $1 for 30 consecutive trading days, then the exchange will initiate the delisting process".

a critical role in the withdrawal decision,[59] we attempt to provide more evidence on the affect of underwriter quality on the decision to issue or withdraw an SEO. First, we ask whether underwriter quality affect the impact of the different components of filing period returns. This would provide insight into whether underwriters of different quality use different information sets. We operationalize this by defining indicator variables that equal one for filings with low ranked underwriters. Specifically, we set LowRank1 equal to one for SEOs with underwriter rankings less than or equal to 7, and zero otherwise. We also completely remove SEOs with underwriter ranking between 6 and 8 and define LowRank2 as a dummy variable equals one for SEOs with underwriter rankings less than or equal to 6, and zero otherwise. We then interact the indicator variables and interact it with the cumulative firm prediction errors, market prediction errors, and industry returns.

Table 3.5 presents the results. The point estimate on the non-interacted return components show how firm specific, industry, and market wide returns affect the issuance decision for firms with high quality underwriters. Separating by underwriter quality allows us to see that firms with higher quality underwriters use firm specific information when making he decision to issue or withdraw. Higher idiosyncratic filing period returns increase the likelihood of issuing in the face of negative filing period returns. For firms with low quality underwriters, firm specific information does not significantly affect the issuance decision. Industry level returns play a major role even for firms with high quality underwriters. Market wide information still positively affects the likelihood of issuing, but its statistical significance is reduced. Underwriter quality does not significantly affect the

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[59] For example, in Edelen and Kadlec's (2005) model, they assume that underwriters hold the withdrawal options, and in fear of being withdrawn by underwriters, issuers are willing only partially to incorporate favorable market information into the offer prices. Busaba, Liu, and Restrepo (2019) show that underwriters may deliberately price up weakly demanded IPOs to prevent withdrawals. Lee and Masulis (2009) claim that underwriters have a stronger voice than issuers in SEO withdrawal decisions.

impact of industry and market wide information on the issuance decision. Overall, these results suggest that higher quality underwriters use more information when making the issue/withdraw decision.[60]

3.4.3 Delisting and Reverse Splits after Issuances and Withdrawals

We now look at the period following issuances and withdrawals to see whether issuing affects delisting's and reverse splits. Issuing increases market capitalization which will move firms away from capitalization-based listing cut offs. This should result in fewer delisting's for issuing firms. Issuing also increases the public float which allows issuers to manage price-based listing requirements with fewer concerns that reverse splits will trigger delisting based on public float criteria.

We assess whether issuing rather than withdrawing affects delisting using linear probability models. We define "delisting" as delisting codes on CRSP between [300, 599] (*Exchanges, liquidation, and dropped*) to measure delisting events that are due to financial reasons other than mergers and acquisitions. [61] The dependent variables equal one if a sample firm delists within 2, 3, 4, and 5 years after its decision to issue or withdraw. In addition to an indicator variable (SD) is a dummy variable that equals one for SD SEOs and zero for withdrawn, we include the same set of control variables as in the SD completion regressions in Table 3.3. The results are in Table 3.6

Table 3.6 shows that SD SEOs are less likely to delist within two years of the issue/withdraw decision compared to withdrawn SEOs. The estimated coefficient on the SD dummy when we model delisting within two years of the issuance decision is -0.028% and

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[60] We acknowledge that firms with better management may be able to attract better underwriters and these results could be driven by mangers who use better information rather than by the underwriters using better information.

[61] Untabulated results show that includes the delisting events with delisting codes [200, 599] does not change our results.

significant at the 5% level, suggesting that on average SD SEO firms are 2.8% less likely to delist than are firms that withdraw their offerings in the first two years following the issuance/withdrawal decision. The 2.8% difference is economically meaningful as the unconditional probability of delisting in the in the two years following the decision is 4.2%. The survival benefits are short-lived. By the third year following the issuance decision whether firms issued or withdrew no longer affects the likelihood of delisting.

Completing rather than withdrawing offerings lowers the probability of delisting in the short-run. This is consistent with our hypothesis that SD managers issue to in the face of negative filing period returns to forestall delisting. The results also indicate that this is at best a temporary solution.

We next look at reverse split activity in the period following the issue/withdraw decision. The extreme negative filing period returns push our SD and withdraw firms closer to any price-based delisting thresholds. Reverse splits mechanically increase share price, but listing requirements based on public float limit firms ability to use this tool. [62] Completing SEOs boosts the number of shares outstanding which facilitates using reverse split to move away from price-based listing thresholds. If issuance is related to delisting concerns, we expect SD firms to engage in reverse split activity following their issuances.

We compare the reverse split activity of SD and withdraw firms using an endogenous treatment effect model. Since the choice of completion or withdrawal is not random simply regressing future reverse split activities on the SD dummy would yield biased estimates. The endogenous treatment effect model consists of two equations: an equation for the

[62] For example, the current public float threshold for Nasdaq Capital Market Companies is 500,000 shares.

outcome Y_i (reverse split activity), and an equation for the treatment effect I_i^* (SD vs. withdraw):

The endogenous treatment effect model consists of two equations: an equation for the outcome Y_i, and an equation for the treatment effect I_i^*:

$$Y_i = X_i\beta + \delta I_i^* + \varepsilon \tag{3.8}$$

$$I_i^* = \begin{cases} 1, & if\ W_i\gamma + \mu > 0 \\ 0, & otherwise \end{cases} \tag{3.9}$$

Where, X_i and W_i are the covariates for the outcome and treatment stages. We use the two-step control-function estimation. Specifically, we use two measures for firm i's future reverse split activities as the dependent variable Y_i in the outcome stage: (1) a dummy variable equals one if firm i conducts at least one reverse split three years following SEO issuances (withdrawals), and (2) the total number of reverse splits firm i conducts in the three years following the issue/withdraw decision. The dependent variable I_i^*, in the treatment stage, is the endogenous variable, which is a dummy variable equals one for SD SEOs and zero for withdrawn SEOs.

A plausible instrumental variable in the treatment stage is the underwriter ranking. As shown in the underwriter ranking section above, underwriter quality strongly affects the SEO completion decisions. At the same time, underwriters are selected prior to the filing and thus are unlikely related to the filing period returns. There is also no direct link between underwriters selected prior to filing and reverse splits following the decision to complete.[63]

[63] Non-tabulated results show that the link between delisting related variables and the issuance decision are not related to underwriter quality.

Therefore, we argue that underwriter ranking is a valid instrument variable for post-SEO reverse split decisions in the endogenous treatment effect regression.

Table 3.7 reports the results. We use the same set of control variables in Table 3.3 and include the exchange-by-year fixed effects and industry-by-year fixed effects in the outcome stage.[64] The estimates on the SD dummies are positive and significant at the 1% level in both Columns (1) and (2). These results are consistent with our hypothesis that SD SEOs are more likely to engage in reverse splits after SEOs. Moreover, the estimated coefficients on the lambdas are negative and significant in both models. This suggesting that unobservable factors that increase reverse splits tend to correlate with factors that decrease the propensity of SD SEO completions. Taken together, SD SEOs have a higher propensity to conduct reverse splits after SEO completions, consistent with our conjecture that delisting concerns increase the likelihood of SD issuances.

3.4.4 Market Reactions to Issuance and Withdrawal Decisions

In this section we provide evidence on the market reaction to the decision to issue in the face of negative filing period returns. Mikkelson and Partch (1988) report that the average market response to withdraw decisions is positive and the average response to issuances is negative. We note that Mikkelson and Partch look at all issuances while we are considering issuances following significantly negative filing period returns. For this group, the evidence so far indicates SD firms face better industry conditions and that issuing facilitates maintenance of their listings. Each of these seem beneficial.

[64] The etregress command in Stata does not allow clustered standard errors, so we do not cluster standard errors by industry.

We measure the cumulative stock returns on days (-1,+6) around issue (withdrawn) dates by using the market adjusted returns.[65] The average abnormal returns on days (-1,+6) for firms that issue following negative filing period returns is -1.52%. This is statistically significant. The average CAR(-1,+6) for firms that withdraw is +8 basis points and is insignificantly different form zero. The first of these results is consistent with Mikkelson and Partch (1988). Before we can conclude that issuing in the face of negative filing period returns is a bad decision, we need an estimate of the CAR(-1,+6) had the issuing firms withdrew. Similarly, before we can conclude that the withdraw decision did not add value, we require an estimate of CAR(-1,+6) had the withdrawing firms issued.

The simple approach to of comparing average CAR(-1,+6) may yield biased estimates because the stock reactions and the completion decisions are endogenously determined. We address this endogeneity problem by using an endogenous switching model that accounts for the selection bias behind the completion decisions. We begin with the methodology of the endogenous switching model and then present the results.

The endogenous switching model is a variant of the traditional Heckman selection model. Let the selection equation for the completion/withdraw decisions be

$$I_i^* = \gamma Z_i + \mu_i \ with \ I_i = \begin{cases} 1 \ if \ I_i^* > 0 \\ 0 \ if \ I_i^* \leq 0 \end{cases} \tag{3.10}$$

where $I_i = 1$ for firms choose to complete after substantial price drops (SD SEOs), $I_i = 0$ for firms choose to withdraw. Z_i is a vector of variables that determines firms' issue

[65] We measure CARs(-1,+6) by price(6)/price(-1)-total market value(6)/total market value(-1). We use a longer window to remove any price pressure effects caused by the issue itself.

or withdrawn decisions after substantial price drops. We include the same control variables in the SD SEO completion decisions (Table 3.3).

Let Y_{1i} be the CARs(-1,+6) on SD SEOs' issue dates and let Y_{2i} be the CARs(-1,+6) on withdrawn SEOs' withdrawn dates.

$$\begin{aligned} &Regime1 : Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \quad if\ I_i = 1 \\ &Regime2 : Y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \quad if\ I_i = 0 \end{aligned} \tag{3.11}$$

where, X_i represents a vector of control variables in the outcome stage, including CARs on the SEO filing dates, filing-period industry returns, and the distance between filing dates and issue (withdrawn) dates.

This modeling choice allows us to estimate counterfactuals.[66] That is, we can estimate the average CAR(-1,+6) for SD firms under the assumption that they has selected to withdraw and we can estimate the CAR(-1,+6) for withdrawn firms under the assumption that they completed their SEO. We then can calculate the effects of treatment (SD SEOs' completion decisions) on the treated (denoted as "TT") as the difference between SD SEOs' actual CARs(-1,+6) and their counterfactual CARs(-1,+6). Similarly, we define the effects of the treatment on the untreated (denoted as "TU") as the difference between withdrawn SEOs' counterfactual CARs(-1,+6), assuming that they could have completed and their actual CARs(-1,+6) on the withdrawn dates.

$$\begin{aligned} TT &= E(Y_{1i} \mid I_i = 1, X_{1i}) - E(Y_{2i} \mid I_i = 1, X_{2i}) \\ TU &= E(Y_{1i} \mid I_i = 0, X_{1i}) - E(Y_{2i} \mid I_i = 0, X_{2i}) \end{aligned} \tag{3.12}$$

[66] See Chapter 9 of Maddala (1985).

Each estimate informs us as to whether the firm is better or worse off for making its choice.

Panel B of Table 3.8 presents the results. Item (a) is the average CAR(-1,+6) for SD SEOs that complete (-1.52% as reported above). Item (b) is the average CAR(-1,+6) for withdrawing firms measured over the window around their decision to withdraw (+8 basis points as reported above). Item (c) is the estimated average CAR(-1.+6) for SD firms that issued under the counterfactual condition that they withdrew. This estimate is -4.48%. The statistically significant difference between the actual and counterfactual CAR(-1,+6) for SD firms indicates that these firms would have been worse off by 2.94% had they chosen to withdraw. Despite being met with a negative return, for issuing firms, issuance is a better decision than withdrawal. Likewise, for the withdrawing firms, had they decided to issue instead, the market reaction would have been -19.8%.

3.5 Conclusion

We observe that the majority of firms facing large negative returns during the filing period of their SEOs chose to complete rather than withdraw their offerings. This leads us to ask why some SEOs are not withdrawn. We present evidence that the decision is not linked to differences in overvaluation at the time firms decide to issue or withdraw. Both issuing and withdrawing firms face significantly negative abnormal returns in the three-year period following their decisions. There is no difference between the long-run abnormal returns.

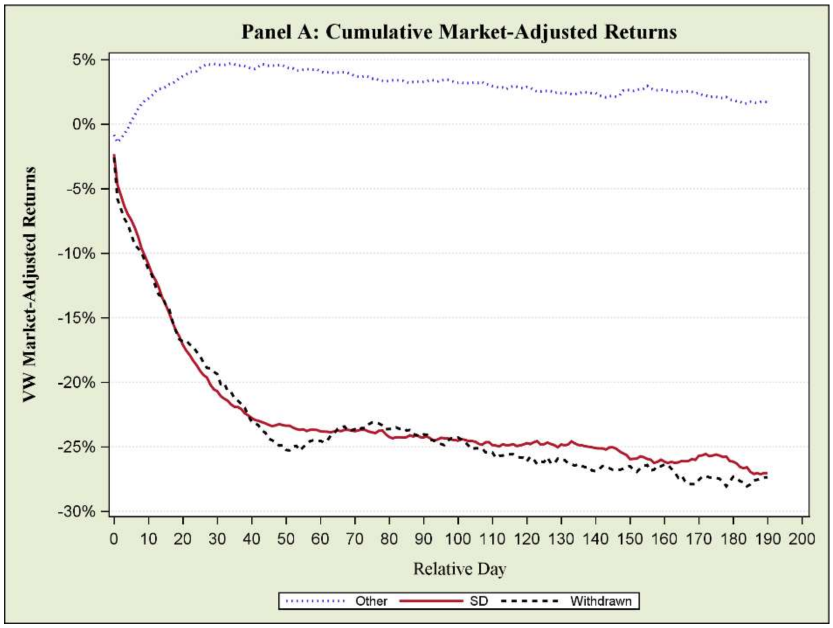
We estimate the roles played by idiosyncratic, industry, and market wide returns in managers' decisions. Interestingly, despite the presence of firm level information, market wide and industry conditions affect the decision to issue or withdraw. The role played by market and industry level information in this setting is consistent with withdrawing firms' frequent citation industry conditions when announcing their decisions. It also suggests that the lack of idiosyncratic firm information may not seriously affect studies of IPO withdrawal.

Finally, we provide evidence that the decision to issue rather than withdraw is a defence against delisting. Completing an SEO boosts market capitalization, the value of public float, and the number of shares outstanding. The last of those helps maintain a minimum bid price by facilitating reverse splits. We find that firms that are closer to delisting or have a higher estimated likelihood of delisting are more likely to complete rather than withdraw their SEO. We also show that completing firms have a lower probability of delisting in the two years following issuance and are more likely to engage in reverse splits following the issuance.

Despite the evidence that issuing provides benefits, the unconditional abnormal returns of issuing firms is negative and significant. We perform an analysis of the counterfactual and show that had the issuing firms decided to withdraw the market reaction would have been significantly more negative. We also show that withdrawing firms would have suffered larger abnormal returns had they decided to issue. These results are consistent with both SD and withdrawing firms making optimal issuing decisions in the face of negative filing period returns.

Figure 3.1: 270-day Post-filing Market-adjusted Stock Returns and Fama-French 49 Industry Returns

Panel A and B present the cumulative market-adjusted stock returns and Fama-French 49 industry returns respectively for Other, SD, and withdrawn SEOs. It plots the returns for 270 calendar days after SEO filings. T=0 represents SEO filing dates.



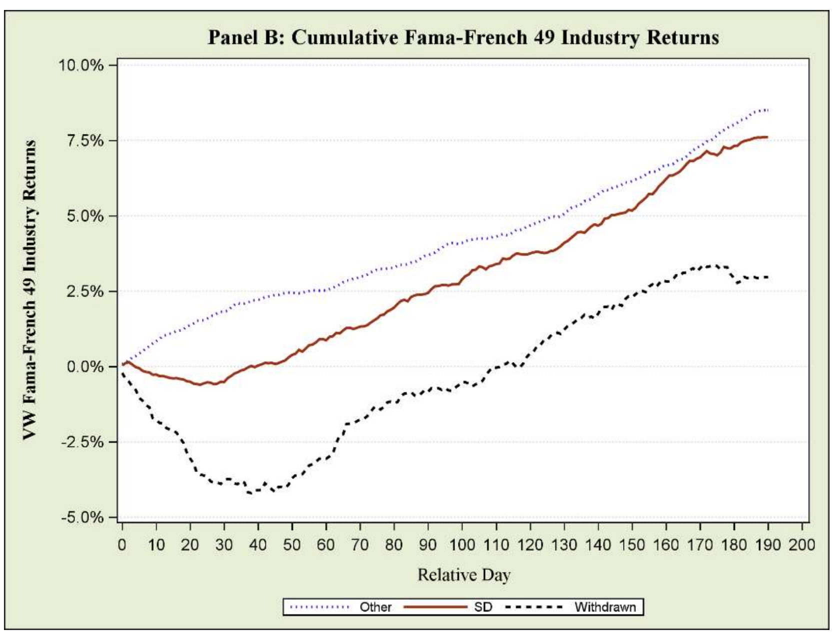


Figure 3.2: 1095-calendar-day Post-issuance (withdrawal) Market-adjusted Stock Returns (including delisting returns)

This figure presents the cumulative market-adjusted stock returns for Other, SD, and withdrawn SEOs. We plot the returns for 1095 calendar days after SEO issuances (withdrawals). T=0 represents SEO issuance (withdrawal) dates.

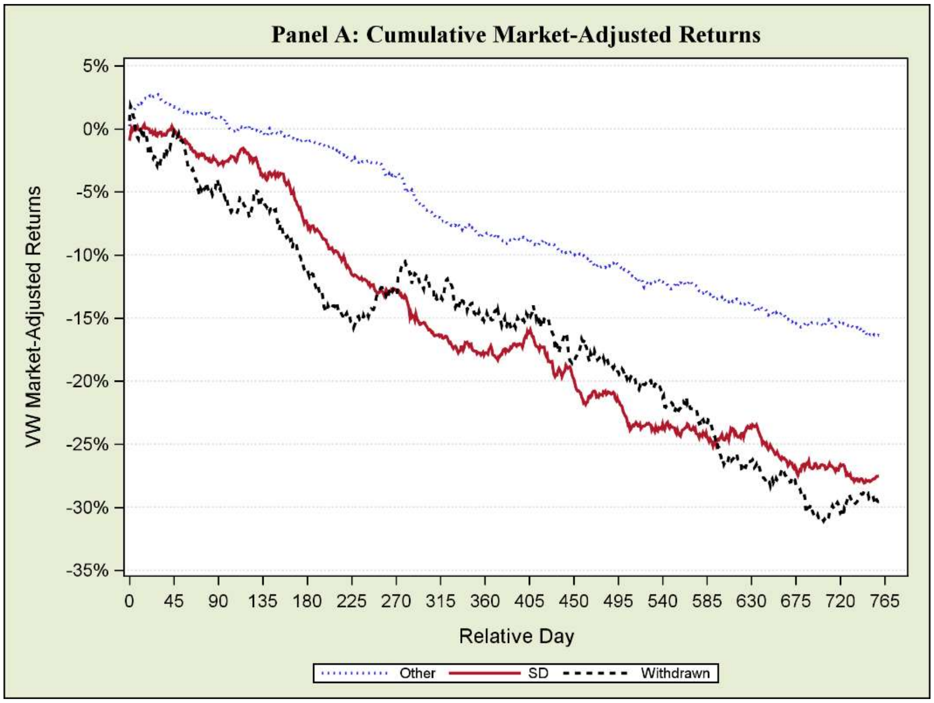


Table 3.1
Summary Statistics

This table reports summary statistics for the SEO sample. The full sample contains 4,654 completed non-shelf SEOs and 232 withdrawn SEOs with filing-periods longer than 90 days between 1984-2016. The completed SEO sample is further sorted into two groups based on the filing-period market-adjusted returns. SD SEOs are defined as the bottom quintile, and Other SEOs are defined as the rest four quintiles. FP Market-Adj Returns are filing-period market-adjusted returns, calculated between filing dates and one day before the issue (withdrawn) dates. Cumulative FAPE and Cumulative MAPE are cumulative filing-period firm and market prediction errors. To estimate FAPE, we regress firm returns on the daily value-weighted Fama-French 49 industry returns and the daily value-weighted CRSP market returns 250 and 20 days before SEO filing dates to extract market and industry betas. Cumulative FAPE is the cumulative daily prediction errors (firmret-mktret*βmkt-indret*βind) over the filing period. To estimate MAPE, we regress the daily value-weighted CRSP market returns on the daily value-weighted Fama-French 49 industry returns 250 and 20 days before SEO filing dates. Cumulative MAPE is the cumulative daily filing-period prediction errors (Mktret-indret*βind). Cumulative Industry Returns is the cumulative value-weighted Fama-French 49 industry returns over the filing period. Cash Needs (Ex-post) is the opposite value of the pro forma cash levels, assuming that a firm does not receive proceeds from the SEO and is estimated by the closest fiscal year after SEO issuances (withdrawals). Distance-to-Delisting is the ratio of average of market capitalization over the standard deviation of market capitalization, which is estimated by 180 days before the SEO filing dates. 180-day Avg Price is the average split-adjusted stock price. Prob(Delisting) is the ex-ante probability of delisting before SEO filings, following the methodology in Campbell, Hilscher, and Szilagyi (2008). Non-Institutional Ownership is the one minus institutional ownership ratio, following the investor demand elasticity measure in Gao and Ritter (2010). Following Lee and Masulis (2009), Net Filing Proceeds is the filing amount minus underwriter fee for completed offers and filing amount for withdrawn offers. Underwriter Rankings are the Carter & Manaster reputation measure. Filing-period distance is the number of days between SEO filings and SEO issuances (withdrawals). Accruals/Assets is from Financial Ratio Suite. Cash Flow/Assets is the sum of net income and depreciation and amortization, scaled by total assets. Listing Age is the number of years since IPOs. Credit Rating is a dummy variable equals one if the issuer has any rated bonds in the year prior to SEO filings. All variables except Cash Needs (Ex-post) are estimated by the closet fiscal year-end and are winsorized at 1% and 99% level. Non-Institutional Ownership is winsorized between [0,1]. The last three columns report the p-values for the differences between SD, Other, and Withdrawn SEOs.

	Full Sample		SD		Other		Withdrawn			Difference	
	Mean	N	Mean	N	Mean	N	Mean	N	SD-Other	SD-WD	Other-WD
FP Market-Adj Returns	-3.64%	4879	-23.86%	931	2.56%	3724	-22.66%	224	(0.000)	(0.134)	(0.000)
Filing Date CARs(-1,+1)	-3.04%	4776	-5.27%	898	-2.29%	3650	-6.28%	228	(0.000)	(0.079)	(0.000)
Cumulative FAPE	-10.30%	4845	-28.76%	921	-4.57%	3701	-29.21%	223	(0.000)	(0.661)	(0.000)
Cumulative MAPE	-0.06%	4849	0.23%	922	-0.13%	3704	-0.07%	223	(0.000)	(0.216)	(0.737)
Cumulative Industry Returns	0.92%	4870	0.12%	929	1.38%	3718	-3.40%	223	(0.000)	(0.000)	(0.000)
Cash Needs(Ex-post)	0.02	4815	0.03	918	0.03	3670	-0.06	227	(0.604)	(0.000)	(0.000)
Distance-to-Delisting	7.12	4869	6.45	925	7.32	3713	6.59	231	(0.000)	(0.638)	(0.018)
180-day Avg Price	28.40	4870	37.23	927	25.12	3712	45.62	231	(0.000)	(0.223)	(0.000)
Prob(Delisting)	0.86%	4526	1.08%	836	0.81%	3470	0.94%	220	(0.000)	(0.242)	(0.311)
Prob(Pre-SEO Reverse Split)	1.43%	4886	2.36%	931	1.21%	3724	1.30%	231	(0.008)	(0.319)	(0.903)
Non-Institutional Ownership	65.44%	4886	72.97%	931	63.33%	3724	69.20%	231	(0.000)	(0.022)	(0.000)
Fraction of Secondary Shares	18.16	4870	15.02	931	18.82	3724	20.19	215	(0.000)	(0.006)	(0.458)
ln(Net Filing Proceeds)	3.86	4464	3.73	879	3.89	3364	3.99	221	(0.000)	(0.002)	(0.168)
Underwriter Rankings	7.82	4607	7.34	878	7.94	3511	7.77	218	(0.000)	(0.002)	(0.105)

Filing-period Distance	31.97	4886	40.12	931	29.31	3724	42.06	231	(0.000)	(0.192)	(0.000)
Accruals/Assets	0.02	4830	0.05	925	0.02	3675	0.03	230	(0.000)	(0.412)	(0.257)
Assets	668.19	4886	282.02	931	785.74	3724	329.54	231	(0.009)	(0.706)	(0.232)
Leverage	0.24	4886	0.22	931	0.24	3724	0.23	231	(0.018)	(0.620)	(0.466)
M/B	4.98	4874	5.83	926	4.77	3717	4.89	231	(0.002)	(0.206)	(0.845)
Cash Flow/Assets	-0.03	4880	-0.14	930	-0.01	3720	-0.07	230	(0.000)	(0.031)	(0.001)
Cash/Assets	0.25	4883	0.32	931	0.23	3722	0.27	230	(0.000)	(0.018)	(0.017)
Listing Age	7.17	4886	5.73	931	7.53	3724	7.09	231	(0.000)	(0.035)	(0.560)
Credit Rating	0.13	4886	0.07	931	0.15	3724	0.13	231	(0.000)	(0.007)	(0.408)
Altman's Z-Score	0.71	4862	-0.42	924	1.02	3709	0.24	229	(0.000)	(0.076)	(0.000)
Ohlson's O-Score	-0.58	4884	-0.32	931	-0.65	3722	-0.53	231	(0.000)	(0.307)	(0.399)

Table 3.2

3-Year SEO Long-Run Stock Performance

This table reports 3-year SEO long-run underperformance using calendar-time portfolio approach. An SEO is included in the event portfolio in month t+1 following SEO issuances (withdrawals). Panel A reports the alphas for SD, Other and WD SEOs using three models: 1) Purged Fama-French three factor model, 2) Purged Fama-French three factor and Purged Investment factor model, and 3) Purged Fama-French Five factor model. Following Loughran and Ritter (2000), we create purged factors by excluding firms that conducted IPOs or SEOs in the past 60 months. Panel B presents the tests of differences in alphas. α(WD)=α(SD), α(Other)=α(SD), α(Other)=α(WD) represent three portfolios that 1) Long WD and Short SD, 2 Long Other and Short SD), and 3) Long Other and Short WD. We follow Speiss and Affleck-Graves (1999) and employ weighted-least-squares with weights equal to the number of firms in each portfolio-month. SD SEOs are the completed SEOs fall on the bottom quintile of idiosyncratic component of filing-period returns. Other SEOs are the rest four quintiles. WD SEOs are the withdrawn SEOs. P-values are reported in the parentheses.

Panel A: Alphas for Calendar-time Portfolios

	Model 1 Purged FF3F	Model 2 Purged FF3F & Invt	Model 3 Purged FF5F	N
α(SD)	-0.8616	-0.7598	-0.4768	409
	(<.001)	(<.001)	(0.025)	
α(WD)	-0.8288	-0.7433	-0.6828	333
	(0.011)	(0.024)	(0.046)	
α(Other)	-0.5268	-0.3887	-0.2293	414
	(<.001)	(0.008)	(0.087)	

Panel B: Test the Differences in Alphas

	Model 1 Purged FF3F	Model 2 Purged FF3F & Invt	Model 3 Purged FF5F	N
α(WD)−α(SD)	-0.0714	-0.0895	-0.2825	333
	(0.806)	(0.762)	(0.352)	
α(Other)−α(SD)	0.2990	0.3512	0.2882	409
	(0.054)	(0.026)	(0.074)	
α(Other)−α(WD)	0.3470	0.4100	0.5174	333
	(0.188)	(0.127)	(0.059)	

Table 3.3

SD SEO Completion Decisions

This table reports the completion decisions between SD SEOs and withdrawn SEOs in the linear probability model. The dependent variable equals one for SD SEOs and zero for withdrawn SEOs. Cumulative FAPE and Cumulative MAPE are cumulative filing-period firm and market prediction errors. To estimate FAPE, we regress firm returns on the daily value-weighted Fama-French 49 industry returns, and the daily value-weighted CRSP market returns 250 and 20 days before SEO filing dates to extract market and industry betas. Cum FPE is the cumulative daily prediction errors (firmret-mktret* mkt-indret* ind) over the filing period. To estimate MPE, we regress the daily value-weighted CRSP market returns on the daily value-weighted Fama-French 49 industry returns 250 and 20 days before SEO filing dates. CumMPE is the cumulative daily filing-period prediction errors (Mktret-indret* ind). Cumulative Industry Returns is the cumulative value-weighted Fama-French 49 industry returns over the filing period. Cash Needs (Ex-post) is the opposite value of the pro forma cash levels, assuming that a firm does not receive proceeds from the SEO and is estimated by the closest fiscal year after SEO issuances (withdrawals). Distance-to-Delisting is the ratio of the average of market capitalization over the standard deviation of market capitalization, which is estimated by 180 days before the SEO filing dates. 180-day Avg Price is the average split-adjusted stock price. Prob(Delisting) is the ex-ante probability of delisting before SEO filings, following the methodology in Campbell, Hilscher, and Szilagyi (2008). Non-Institutional Ownership is the one minus institutional ownership ratio, following the investor demand elasticity measure in Gao and Ritter (2010). Underwriter Rankings are the Carter & Manaster reputation measure. Filing-period distance is the number of days between SEO filings and SEO issuances (withdrawals). Accruals/Assets is from Financial Ratio Suite. Cash Flow/Assets is the sum of net income and depreciation and amortization, scaled by total assets. Listing Age is the number of years since IPOs. Credit Rating is a dummy variable equals one if the issuer has any rated bonds in the year prior to SEO filings. All variables except Cash Needs (Ex-post) are estimated by the closet fiscal year-end and are winsorized at 1% and 99% level. Non-Institutional Ownership is winsorized between [0,1]. Robust standard errors are clustered by Fama-French 49 industries and p-values are reported in the parentheses.

	SD=1 Withdrawn=0				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Cumulative FPE	0.0840	0.1493	0.1850	0.1707	0.1550
	(0.732)	(0.556)	(0.352)	(0.503)	(0.449)
Cumulative Industry Returns	1.3980	1.3992	1.3054	1.4093	1.3154
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cumulative MPE	1.3564	1.2644	1.0299	1.4403	1.0012
	(0.058)	(0.070)	(0.057)	(0.048)	(0.079)
Distance-to-Delisting		-0.0096	-0.0129		
		(0.012)	(0.000)		
180-day Avg Price		-0.0003	-0.0004		
		(0.050)	(0.035)		
Prob(Delisting)				2.2960	3.1511
				(0.002)	(0.029)
Prob(Pre-filing Reverse Split)		0.0020	-0.0156	-0.1220	-0.0802
		(0.983)	(0.875)	(0.322)	(0.556)
Cash Needs(Ex-post)			0.3962		0.4048
			(0.000)		(0.000)
Underwriter Ranking			-0.0271		-0.0234
			(0.001)		(0.002)

Table 3 continues on the next page

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Fraction of Secondary Shares			-0.0003		0.0001
			(0.797)		(0.938)
Non-Institutional Ownership			-0.0271		-0.0472
			(0.818)		(0.756)
Ln(Filing-period Distance)			-0.0498		-0.0665
			(0.253)		(0.191)
Accruals/Assets			-0.0445		-0.0571
			(0.594)		(0.602)
Ln(Assets)			0.0062		0.0084
			(0.733)		(0.630)
Leverage			-0.0405		0.0417
			(0.608)		(0.654)
M/B			0.0049		0.0038
			(0.000)		(0.002)
Cash Flow/Assets			0.1153		0.1153
			(0.002)		(0.047)
Cash/Assets			0.3223		0.3114
			(0.000)		(0.000)
Listing Age			0.0017		0.0022
			(0.511)		(0.410)
Credit Rating			-0.0494		-0.1137
			(0.525)		(0.102)
Constant	0.8421	0.9339	1.2359	0.8402	1.1251
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	887	885	821	794	741
R-squared	0.2853	0.2933	0.3693	0.2962	0.3767
Exchange-by-Year FE	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes
Cluster by	Industry	Industry	Industry	Industry	Industry

Table 3.4
SD SEOs Completion Decisions and Financial Distress

This table reports the completion decisions between SD SEOs and withdrawn SEOs in the linear probability model by including financial distress measures. The dependent variable equals one for SD SEOs and zero for withdrawn SEOs. Altman's Z-Score is calculated as (1.2×working capital + 1.4×retained earnings + 3.3×EBIT + 0.999×sales) / total assets. Ohlson's O-Score is calculated as -1.32 - 0.407×log(total assets) +6.03×total liability/total assets -1.43×working capital/total assets +0.076×current liabilities/current assets – 1.72×D(if total liabilities>total assets) -2.37×net income/total assets -1.83×funds from operations/total liabilities + 0.285×D(if a net loss for the last two years) -0.521×(△net income$_t$)/(|net income$_t$|+|net income$_{t-1}$|). Columns (1)- (4) include the same set of control variables in Table 4. All variables except Cash Needs (Ex-post) are estimated by the closet fiscal year-end and are winsorized at 1% and 99% level. Non-Institutional Ownership is winsorized between [0,1]. Robust standard errors are clustered by Fama-French 49 industries and p-values are reported in the parentheses.

	SD=1 Withdrawn=0			
VARIABLES	(1)	(2)	(3)	(4)
Altman's Z-Score	-0.0017	-0.0008		
	(0.802)	(0.920)		
Ohlson's O-Score			-0.0078	-0.0110
			(0.542)	(0.373)
Distance-to-Delisting	-0.0131		-0.0129	
	(0.000)		(0.000)	
180-day Avg Price	-0.0004		-0.0004	
	(0.034)		(0.032)	
Prob(Delisting)		3.1787		3.3339
		(0.031)		(0.014)
Cumulative FAPE	0.1870	0.1558	0.1850	0.1539
	(0.359)	(0.453)	(0.362)	(0.460)
Cumulative Industry Returns	1.2893	1.2985	1.3143	1.3352
	(0.000)	(0.000)	(0.000)	(0.000)
Cumulative MAPE	0.9660	0.9447	1.0096	0.9610
	(0.078)	(0.107)	(0.072)	(0.109)
Cash Needs(Ex-post)/Assets	0.3899	0.3997	0.3931	0.4003
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.2335	1.1211	1.2399	1.1248
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	815	735	821	741
R-squared	0.3700	0.3766	0.3699	0.3778
Controls	No	Yes	No	Yes
Exchange-by-Year	Yes	Yes	Yes	Yes
Industry-by-Year	Yes	Yes	Yes	Yes
Cluster by	Industry	Industry	Industry	Industry

Table 3.5
Underwriters' Role in SD SEO Completion Decisions

This table reports the role of underwriters' in the completion decisions between SD SEOs and withdrawn SEOs in the linear probability model. The dependent variable equals one for SD SEOs and zero for withdrawn SEOs. Column (1) presents the results in the full sample. LowRank1 is a dummy variable that equals one for SEOs with underwriter ranking below or equals 7. Column (2) excludes the SEOs with underwriter ranking between 6 and 8, and LowRank2 is a dummy variable equals one for SEOs with underwriter ranking below or equals 6. Cumulative FAPE and Cumulative MAPE are cumulative filing-period firm and market prediction errors. Cumulative Indret is the cumulative value-weighted Fama-French 49 industry returns over the filing period. Both columns include the same set of control variables in Table 4. All variables except Cash Needs (Ex-post) are estimated by the closet fiscal year-end and are winsorized at 1% and 99% level. Non-Institutional Ownership is winsorized between [0,1]. Robust standard errors are clustered by Fama-French 49 industries and p-values are reported in the parentheses.

	SD=1 Withdrawn=0	
VARIABLES	Using LowRank1	Using LowRank2
Cumulative FPE	0.3537	0.4914
	(0.093)	(0.012)
Cumulative Indret	1.4283	1.4598
	(0.000)	(0.000)
Cumulative MPE	1.2893	1.2879
	(0.062)	(0.146)
Cumulative FPE*LowRank	-0.6159	-0.7850
	(0.034)	(0.030)
Cumulative Indret*LowRank	-0.3999	-0.8646
	(0.460)	(0.255)
Cumulative MPE*LowRank	-0.9752	-0.8039
	(0.507)	(0.579)
Distance-to-Delisting	-0.0123	-0.0136
	(0.000)	(0.000)
180-day Avg Price	-0.0004	-0.0004
	(0.026)	(0.024)
Cash Needs(Ex-post)/Assets	0.4062	0.3488
	(0.000)	(0.000)
LowRank	-0.1129	-0.1667
	(0.256)	(0.126)
Constant	1.0547	1.1093
	(0.000)	(0.000)
Observations	821	670
R-squared	0.3724	0.4168
Controls	Yes	Yes
Exchange-by-Year	Yes	Yes
Industry-by-Year	Yes	Yes
Cluster by	Industry	Industry

Table 3.6
Long-term Delisting Decisions

This table reports SEOs' delisting decisions within 2, 3, 4, and 5 years after SEO issuances (withdrawals) for between SD and withdrawn SEOs. The dependent variable equals one if a SEO delisted (The delisting codes on CRSP are between [300, 599]) within 2, 3, 4, and 5 years. SD is a dummy variable equals one for SD SEOs and zero for withdrawn SEOs. All Columns include the same set of control variables as in Table 4. All variables except Cash Needs (Ex-post) are estimated by the closet fiscal year-end and are winsorized at 1% and 99% level. Non-Institutional Ownership is winsorized between [0,1]. Robust standard errors are clustered by Fama-French 49 industries and p-values are reported in the parentheses.

	Delisting			
	2-year	3-year	4-year	5-year
VARIABLES	(1)	(2)	(3)	(4)
SD	-0.0284	-0.0313	-0.0284	-0.0024
	(0.037)	(0.187)	(0.304)	(0.931)
Cumulative FAPE	-0.0027	-0.0421	-0.0740	-0.1129
	(0.975)	(0.641)	(0.465)	(0.384)
Cumulative Industry Returns	0.0105	0.0913	0.1082	0.0919
	(0.957)	(0.790)	(0.742)	(0.776)
Cumulative MAPE	0.2999	0.4227	0.6416	0.9357
	(0.086)	(0.220)	(0.023)	(0.007)
Cash Needs(Ex-post)	0.1322	0.1692	0.1345	0.1810
	(0.113)	(0.044)	(0.354)	(0.158)
Constant	0.0215	-0.0523	-0.0734	-0.1605
	(0.817)	(0.670)	(0.646)	(0.341)
Observations	823	823	823	823
R-squared	0.3189	0.4013	0.3994	0.4105
Controls	Yes	Yes	Yes	Yes
Exchange-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Cluster by	Industry	Industry	Industry	Industry

Table 3.7
3-Year Post-SEO Reverse Split Decisions

This table presents the 3-year post-SEO reverse split decisions between SD and withdrawn SEOs using the endogenous treatment effects model. Columns (1) and (2) report each firm's probability and the number of reverse splits three years following SEO issuances (withdrawals), respectively. RevSplit Dummy equals one if a firm conducts a reverse split in the future. RevSplit Number is the total number of reverse splits each firm conducts after SEO issuances (withdrawals). SD is a dummy variable that equals one for SD SEOs and zero for withdrawn SEOs. Columns (1) and (2) report the outcome stages of the linear regressions with endogenous treatment effects. Table 3.A2 reports the corresponding selection stages. Both columns include the same set of control variables in Table 4. All variables except Cash Needs (Ex-post) are estimated by the closet fiscal year-end and are winsorized at 1% and 99% level. Non-Institutional Ownership is winsorized between [0,1]. Robust standard errors are clustered by Fama-French 49 industries and p-values are reported in the parentheses.

	Outcome Stage	
	RevSplit Dummy	RevSplit Number
VARIABLES	(1)	(2)
SD	0.4135	0.5336
	(0.001)	(0.000)
Cumulative FAPE	-0.0847	-0.0937
	(0.216)	(0.252)
Cumulative Industry Returns	-0.5108	-0.6406
	(0.009)	(0.007)
Cumulative MAPE	-0.2958	-0.3654
	(0.295)	(0.279)
Cash Needs(Ex-post)	-0.0531	-0.0856
	(0.343)	(0.201)
Constant	-0.4177	-0.5441
	(0.172)	(0.137)
Lambda	-0.2516	-0.3247
	(0.000)	(0.000)
Observations	1,055	1,055
Controls	Yes	Yes
Exchange-by-Year FE	Yes	Yes
Industry-by-Year FE	Yes	Yes
Cluster	No	No

Table 3.8
Comparing CAR(-1,+6) on Issue (Withdrawn) Dates

This table reports the CAR(-1,+6) difference on the issuance (withdrawn) dates for SD and withdrawn SEOs in an endogenous switching model. For the selection stage, the dependent variable, SD, is a dummy for SD SEOs, is estimated over a set of variables that can predict the completion decisions between SD and withdrawn SEOs. For the outcome stage, the dependent variable is CAR(-1,+6) on the issue (withdrawn) dates and control variables include CAR(-1,+1) on the announcement dates, cumulative industry returns over the filing period and filing-period distance. Panel A presents the interpretation of the treatment effects in the endogenous switching model, and Panel B reports the results. The last column compares the CAR(-1, 6) differences for SD and withdrawn SEOs with their corresponding counterfactual CARs. P-values are reported in parentheses.

Panel A: Interpretation of the Treatment Effects

Subsamples	To complete	Not to complete	Difference
SD SEOs	(a) $E\left(Y_{1i} \mid I_i = 1\right)$	(c) $E\left(Y_{2i} \mid I_i = 1\right)$	TT
Withdrawn SEOs	(d) $E\left(Y_{1i} \mid I_i = 0\right)$	(b) $E\left(Y_{2i} \mid I_i = 0\right)$	TU

Ii: 1 if an SEO was SD, 0 if an SEO was withdrawn

Y1i: CAR(-1,+6) if an SEO was SD

Y2i: CAR(-1,+6) if an SEO was withdrawn

TT: treatment effects of CAR(-1,+6) between SD SEOs and SD that could have withdrawn

TU: treatment effects of CAR(-1,+6) between withdrawn SEOs and withdrawn that could have completed

Panel B: CAR(-1,+6) Differences on the Issue (Withdrawn) Dates

Subsamples	To complete	Not to complete	Difference
SD SEOs	(a) -1.524%	(c) -4.483%	TT: (<.001)
Withdrawn SEOs	(d) -19.814%	(b) 0.075%	TU: (<.001)

Table 3.A1

Logit Model of Estimating the Ex-ante Delisting Probability

This table reports the logit model of firm's delisting decisions. The dependent variable equals one if a firm delists within one year. Following Campbell, Hilscher, and Szilagyi (2008), we scale net income, total liability, and cash by the market value of total assets. Excess return is firm in excess of S&P market returns. Relative size is the log value of the market value of equity over the total S&P market size. P-values are reported in the parentheses.

	(1)	(2)
	1980-2019	1980-2003
	Prob(Dlst)	Prob(Dlst)
VARIABLES	Logit	Logit
Net Income/Mkt Value of Assets	-6.7743	-7.7713
	(0.000)	(0.000)
Total Liability/Mkt Value of Assets	1.5999	1.4538
	(0.000)	(0.000)
Excess Returns	-0.6290	-0.6170
	(0.000)	(0.000)
Volatility	11.2089	13.4425
	(0.000)	(0.000)
Relative Size	-0.3315	-0.3166
	(0.000)	(0.000)
Cash/Mkt Value of Assets	-0.8239	-1.2532
	(0.000)	(0.000)
Market-to-Book Ratio	0.1937	0.1939
	(0.000)	(0.000)
Price	-0.6314	-0.5129
	(0.000)	(0.000)
Constant	-10.6006	-10.4978
	(0.000)	(0.000)
Observations	672,321	421,077
Robust Stderr	Yes	Yes
Psudo-R2	32.9%	32.1%

Table 3.A2
3-Year Post-SEO Reverse Split Decisions (Selection Stages)

This table presents the 3-year post-SEO reverse split decisions between SD and withdrawn SEOs using the endogenous treatment effects model. The dependent variables are SD dummy that equals one for SD SEOs and zero for withdrawn SEOs. This regression model includes the same set of control variables in Table 4. All variables except Cash Needs (Ex-post) are estimated by the closet fiscal year-end and are winsorized at 1% and 99% level. Non-Institutional Ownership is winsorized between [0,1]. Robust standard errors are clustered by Fama-French 49 industries and p-values are reported in the parentheses.

	Selection Stage
	SD
VARIABLES	(1)
CumFPE	0.4487
	(0.226)
CumIndRet	4.3834
	(0.000)
CumMPE	2.6601
	(0.074)
Reverse Split Dummy	0.1826
	(0.633)
Cash Needs(Ex-post)	1.3989
	(0.000)
Underwriter Ranking	-0.0503
	(0.155)
Fraction of Secondary Shares	-0.0004
	(0.840)
Non-Institutional Ownership	-0.1410
	(0.587)
Ln(Filing-period Distance)	-0.1580
	(0.068)
Accruals/Assets	0.1894
	(0.497)
Ln(Assets)	-0.0713
	(0.207)
Leverage	0.2333
	(0.370)
M/B	0.0030
	(0.630)
Cash Flow/Assets	0.3876
	(0.028)
Cash/Assets	1.1191
	(0.000)
Listing Age	0.0027
	(0.658)
Credit Rating	0.0159
	(0.937)
Constant	2.0625
	(0.000)
Observations	1,055
R-Squared	0.3109
Controls	Yes

Reference

Acharya, Viral, and Zhaoxia Xu. "Financial dependence and innovation: The case of public versus private firms." *Journal of Financial Economics* 124, no. 2 (2017): 223-243.

Akhigbe, Aigbe, Stephen F. Borde, and Ann Marie Whyte. "Does an industry effect exist for initial public offerings?" *Financial Review* 38, no. 4 (2003): 531-551.

Alderson, Michael J., and Brian L. Betker. "The long-run performance of companies that withdraw seasoned equity offerings." *Journal of Financial Research* 23, no. 2 (2000): 157-178.

Altı, Aydoğan, and Johan Sulaeman. "When do high stock returns trigger equity issues?" *Journal of Financial Economics* 103, no. 1 (2012): 61-87.

Alti, Aydoğan. "How persistent is the impact of market timing on capital structure?." *The Journal of Finance* 61, no. 4 (2006): 1681-1710.

Altınkılıç, Oya, and Robert S. Hansen. "Discounting and underpricing in seasoned equity offers." *Journal of Financial Economics* 69, no. 2 (2003): 285-323.

Asker, John, Joan Farre-Mensa, and Alexander Ljungqvist. "Corporate investment and stock market listing: A puzzle?" *Review of Financial Studies* 28, no. 2 (2015): 342-390.

Autore, Don M, Kumar, Raman, and Dilip K. Shome. "The revival of shelf-registered corporate equity offerings." *Journal of Corporate Finance* 14, no. 1 (2008): 32-50.

Bajo, Emanuele, Thomas J. Chemmanur, Karen Simonyan, and Hassan Tehranian. "Underwriter networks, investor attention, and initial public offerings." *Journal of Financial Economics* 122, no. 2 (2016): 376-408.

Baker, Malcolm, and Jeffrey Wurgler. "Market timing and capital structure." *The Journal of Finance* 57, no. 1 (2002): 1-32.

Bakke, Tor-Erik, Candace E. Jens, and Toni M. Whited. "The real effects of delisting: Evidence from a regression discontinuity design." *Finance Research Letters* 9, no. 4 (2012): 183-193.

Barber, Brad M., and John D. Lyon. "Detecting long-run abnormal stock returns: The empirical power and specification of test statistics." *Journal of Financial Economics* 43, no. 3 (1997): 341-372.

Benveniste, Lawrence M., and Paul A. Spindt. “How investment bankers determine the offer price and allocation of new issues.” *Journal of Financial Economics* 24, no. 2 (1989): 343-361.

Bernstein, Shai. “Does going public affect innovation?” *The Journal of Finance* 70, no. 4 (2015): 1365-1403.

Billett, Matthew T., Mark J. Flannery, and Jon A. Garfinkel. “Frequent issuers’ influence on long-run post-issuance returns.” *Journal of Financial Economics* 99, no. 2 (2011): 349-364.

Blanchard, Olivier Jean, Florencio Lopez-de-Silanes, and Andrei Shleifer. “What do firms do with cash windfalls?” *Journal of Financial Economics* 36, no. 3 (1994): 337-360.

Boeh, Kevin K., and Craig Dunbar. “Underwriter deal pipeline and the pricing of IPOs.” *Journal of Financial Economics* 120, no. 2 (2016): 383-399.

Boone, Audra L., Ioannis V. Floros, and Shane A. Johnson. “Redacting proprietary information at the initial public offering.” *Journal of Financial Economics* 120, no. 1 (2016): 102-123.

Bradley, Daniel J., and Bradford D. Jordan. “Partial adjustment to public information and IPO underpricing.” *Journal of Financial and Quantitative Analysis* (2002): 595-616.

Bradley, Daniel, and Xiaojing Yuan. “Information spillovers around seasoned equity offerings.” *Journal of Corporate Finance* 21 (2013): 106-118.

Brau, James C., and Stanley E. Fawcett. “Initial public offerings: An analysis of theory and practice.” *The Journal of Finance* 61, no. 1 (2006): 399-436.

Brau, James C., Robert B. Couch, and Ninon K. Sutton. “The desire to acquire and IPO long-run underperformance.” *Journal of Financial and Quantitative Analysis* (2012): 493-510.

Braun, Matias, and Borja Larrain. “Do IPOs affect the prices of other stocks? Evidence from emerging markets.” *Review of Financial Studies* 22, no. 4 (2009): 1505-1544.

Brav, Alon, and Paul A. Gompers. “Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and nonventure capital - backed companies.” *The Journal of Finance* 52, no. 5 (1997): 1791-1821.

Brav, Omer. “Access to capital, capital structure, and the funding of the firm.” *The Journal of Finance* 64, no. 1 (2009): 263-308.

Brown, Stephen J., and Jerold B. Warner. “Using daily stock returns: The case of event studies.” *Journal of Financial Economics* 14, no. 1 (1985): 3-31.

Busaba, Walid Y., Zheng Liu, and Felipe Restrepo. "Do Underwriters Price Up IPOs to Prevent Withdrawal?" *Journal of Financial and Quantitative Analysis* (2019): 1-32.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi. "In search of distress risk." *The Journal of Finance* 63, no. 6 (2008): 2899-2939.

Carlson, Murray, Adlai Fisher, and Ron Giammarino. "Corporate investment and asset price dynamics: Implications for the cross - section of returns." *The Journal of Finance* 59, no. 6 (2004): 2577-2603.

Carlson, Murray, Adlai Fisher, and Ron Giammarino. "Corporate investment and asset price dynamics: Implications for SEO event studies and long-run performance." *The Journal of Finance* 61.3 (2006): 1009-1034.

Carter, Richard B., Frederick H. Dark, and Ajai K. Singh. "Underwriter reputation, initial returns, and the long-run performance of IPO stocks." *The Journal of Finance* 53.1 (1998): 285-311.

Carvalho, Daniel. "Financing constraints and the amplification of aggregate downturns." *Review of Financial Studies* 28, no. 9 (2015): 2463-2501.

Celikyurt, Ugur, Merih Sevilir, and Anil Shivdasani. "Going public to acquire? The acquisition motive in IPOs." *Journal of Financial Economics* 96, no. 3 (2010): 345-363.

Chemmanur, Thomas J., and Jie He. "IPO waves, product market competition, and the going public decision: Theory and evidence." *Journal of Financial Economics* 101, no. 2 (2011): 382-412.

Clarke, Jonathan, Craig Dunbar, and Kathleen M. Kahle. "Long-run performance and insider trading in completed and canceled seasoned equity offerings." *Journal of Financial and Quantitative Analysis* (2001): 415-430.

Cochrane, John H. "Production-based asset pricing and the link between stock returns and economic fluctuations." *The Journal of Finance* 46, no. 1 (1991): 209-237.

Cookson, J. Anthony. "Leverage and strategic preemption: Lessons from entry plans and incumbent investments." *Journal of Financial Economics* 123, no. 2 (2017): 292-312.

Corwin, Shane A. "The determinants of underpricing for seasoned equity offers." *The Journal of Finance* 58, no. 5 (2003): 2249-2279.

Corwin, Shane A., and Paul Schultz. "The role of IPO underwriting syndicates: Pricing, information production, and underwriter competition." *The Journal of Finance* 60, no. 1 (2005): 443-486.

Da, Zhi, Joseph Engelberg, and Pengjie Gao. “In search of attention.” *The Journal of Finance* 66, no. 5 (2011): 1461-1499.

Dambra, Michael, Matthew Gustafson, and Kevin Pisciotta. “IPO Size and the Benefits to going Public.” *Working Paper* (2019).

DeAngelo, Harry, Linda DeAngelo, and Rene M. Stulz. “Seasoned equity offerings, market timing, and the corporate lifecycle.” *Journal of Financial Economics* 95, no. 3 (2010): 275-295.

Dittmar, Amy, Ran Duchin, and Shuran Zhang. “The timing and consequences of seasoned equity offerings: A regression discontinuity approach.” *Journal of Financial Economics (2020).*

Doidge, Craig, G. Andrew Karolyi, and René M. Stulz. “The US listing gap.” *Journal of Financial Economics* 123, no. 3 (2017): 464-487.

Dunbar, Craig G., and Stephen R. Foerster. “Second time lucky? Withdrawn IPOs that return to the market.” *Journal of Financial Economics* 87, no. 3 (2008): 610-635.

Easterbrook, Frank H. “Two agency-cost explanations of dividends.” *American Economic Review* 74, no. 4 (1984): 650-659.

Eckbo, B. Espen, and Øyvind Norli. “Liquidity risk, leverage and long-run IPO returns.” *Journal of Corporate Finance* 11, no. 1-2 (2005): 1-35.

Eckbo, B. Espen, Ronald W. Masulis, and Øyvind Norli, “Security Offerings.” Handbook of Empirical Corporate Finance (2007) SET 2, 233–373.

Eckbo, B. Espen, Ronald W. Masulis, and Øyvind Norli. “Seasoned public offerings: Resolution of the ‘new issues puzzle’.” *Journal of Financial Economics* 56, no. 2 (2000): 251-291.

Edelen, Roger M., and Gregory B. Kadlec. “Issuer surplus and the partial adjustment of IPO prices to public information.” *Journal of Financial Economics* 77, no. 2 (2005): 347-373.

Fama, Eugene F., and Kenneth R. French. “The cross-section of expected stock returns.” *The Journal of Finance* 47, no. 2 (1992): 427-465.

Fama, Eugene F., and Kenneth R. French. “Common risk factors in the returns on stocks and bonds.” *Journal of Financial Economics* (1993).

Fama, Eugene F., and Kenneth R. French. “Dissecting anomalies with a five-factor model.” *Review of Financial Studies* 29, no. 1 (2016): 69-103.

Farre-Mensa, Joan, and Alexander Ljungqvist. “Do measures of financial constraints measure financial constraints?." *Review of Financial Studies* 29, no. 2 (2016): 271-308.

Field, Laura Casares, and Michelle Lowry. "Institutional versus individual investment in IPOs: The importance of firm fundamentals." *Journal of Financial and Quantitative Analysis* 44, no. 3 (2009): 489-516.

Field, Laura, Michelle Lowry, and Anahit Mkrtchyan. "Are busy boards detrimental?" *Journal of Financial Economics* 109, no. 1 (2013): 63-82.

Gao, Xiaohui, and Jay R. Ritter. "The marketing of seasoned equity offerings." *Journal of Financial Economics* 97, no. 1 (2010): 33-52.

Gao, Xiaohui, Jay R. Ritter, and Zhongyan Zhu. "Where have all the IPOs gone?" *Journal of Financial and Quantitative Analysis* 48, no. 6 (2013): 1663-1692.

Gilje, Erik P., and Jerome P. Taillard. "Do private firms invest differently than public firms? Taking cues from the natural gas industry." *The Journal of Finance* 71, no. 4 (2016): 1733-1778.

Graham, John R., and Campbell R. Harvey. "The theory and practice of corporate finance: Evidence from the field." *Journal of Financial Economics* 60, no. 2-3 (2001): 187-243.

Grullon, Gustavo, Bradley Paye, Shane Underwood, and James P. Weston. "Has the propensity to pay out declined?" *Journal of Financial and Quantitative Analysis* 46, no. 1 (2011): 1-24.

Gustafson, Matthew. "Price pressure and overnight seasoned equity offerings." *Journal of Financial and Quantitative Analysis* 53(2), pp.837-866 (2018).

Hanley, Kathleen Weiss, and Gerard Hoberg. "The information content of IPO prospectuses." *The Review of Financial Studies* 23, no. 7 (2010): 2821-2864.

Hanley, Kathleen Weiss, and Gerard Hoberg. "Litigation risk, strategic disclosure and the underpricing of initial public offerings." *Journal of Financial Economics* 103, no. 2 (2012): 235-254.

Hanley, Kathleen Weiss. "The underpricing of initial public offerings and the partial adjustment phenomenon." *Journal of Financial Economics*, 34(2), pp.231-250 (1993).

Harford, Jarrad, Jared Stanfield, and Feng Zhang. "Do insiders time management buyouts and freezeouts to buy undervalued targets?" *Journal of Financial Economics* 131, no. 1 (2019): 206-231.

Harford, Jarrad, Sattar A. Mansi, and William F. Maxwell. "Corporate governance and firm cash holdings in the US." *Journal of Financial Economics* 87, no. 3 (2008): 535-555.

Hertzel, Michael G., and Zhi Li. "Behavioral and rational explanations of stock price performance around SEOs: Evidence from a decomposition of market-to-book ratios." *Journal of Financial and Quantitative Analysis* (2010): 935-958.

Hertzel, Michael G., Mark R. Huson, and Robert Parrino. "Public market staging: The timing of capital infusions in newly public firms." *Journal of Financial Economics* 106, no. 1 (2012): 72-90.

Hoberg, Gerard, and Gordon Phillips. "Real and financial industry booms and busts." *The Journal of Finance* 65, no. 1 (2010): 45-86.

Holderness, Clifford G. "Equity issuances and agency costs: The telling story of shareholder approval around the world." *Journal of Financial Economics* 129, no. 3 (2018): 415-439.

Hou, Kewei, and David T. Robinson. "Industry concentration and average stock returns." *The Journal of Finance* 61, no. 4 (2006): 1927-1956.

Hsu, Hung-Chia, Adam V. Reed, and Jörg Rocholl. "The new game in town: Competitive effects of IPOs." *The Journal of Finance* 65, no. 2 (2010): 495-528.

Huang, Rongbing, and Jay R. Ritter. "The puzzle of frequent and large issues of debt and equity." *Journal of Financial and Quantitative Analysis* (2020).

Ikenberry, David, Josef Lakonishok, and Theo Vermaelen. "Stock repurchases in Canada: Performance and strategic trading." *The Journal of Finance* 55, no. 5 (2000): 2373-2397.

Iliev, Peter and Lowry, Michelle, "Venturing beyond the IPO: Financing of newly public firms by pre-IPO investors." *The Journal of Finance* (2020).

Irvine, Paul J., and Jeffrey Pontiff. "Idiosyncratic return volatility, cash flows, and product market competition." *Review of Financial Studies* 22, no. 3 (2009): 1149-1177.

Jensen, Michael C. "Agency costs of free cash flow, corporate finance, and takeovers." *American Economic Review* 76, no. 2 (1986): 323-329.

Kim, Woojin, and Michael S. Weisbach. "Motivations for public equity offers: An international perspective." *Journal of Financial Economics* 87, no. 2 (2008): 281-307.

Lang, Larry HP, and René M Stulz. "Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis." *Journal of Financial Economics* 32, no. 1 (1992): 45-60.

Leary, Mark T., and Michael R. Roberts. "Do peer firms affect corporate financial policy?"

The Journal of Finance 69, no. 1 (2014): 139-178.

Lee, Gemma, and Ronald W. Masulis. "Seasoned equity offerings: Quality of accounting information and expected flotation costs." *Journal of Financial Economics* 92, no. 3 (2009): 443-469.

Liu, Xiaoding, and Jay R. Ritter. "Local underwriter oligopolies and IPO underpricing." *Journal of Financial Economics* 102, no. 3 (2011): 579-601.

Long Jr, John B. "The numeraire portfolio." *Journal of Financial Economics* 26, no. 1 (1990): 29-69.

Loughran, Tim, and Jay R. Ritter. "The new issues puzzle." *The Journal of Finance* 50, no. 1 (1995): 23-51.

Loughran, Tim, and Jay R. Ritter. "Uniformly least powerful tests of market efficiency." *Journal of Financial Economics* 55, no. 3 (2000): 361-389.

Loughran, Tim, and Jay R. Ritter. "Why don't issuers get upset about leaving money on the table in IPOs?" *Review of Financial Studies* 15, no. 2 (2002): 413-444.

Lowry, Michelle, and G. William Schwert. "Is the IPO pricing process efficient?" *Journal of Financial Economics* 71, no. 1 (2004): 3-26.

Lowry, Michelle, Micah S. Officer, and G. William Schwert. "The variability of IPO initial returns." *The Journal of Finance* 65, no. 2 (2010): 425-465.

Lowry, Michelle, Roni Michaely, and Ekaterina Volkova. "Initial public offerings: A synthesis of the literature and directions for future research." *Forthcoming Foundations and Trends® in Finance* (2017).

Lyandres, Evgeny, Le Sun, and Lu Zhang. "The new issues puzzle: Testing the investment-based explanation." *Review of Financial Studies* 21, no. 6 (2008): 2825-2855.

Macey, Jonathan, Maureen O'Hara, and David Pompilio. "Down and out in the stock market: the law and economics of the delisting process." *Journal of Law and Economics* 51, no. 4 (2008): 683-713.

Maddala, Gangadharrao S. "Limited-dependent and qualitative variables in econometrics". No. 3. Cambridge university press, 1985.

Maksimovic, Vojislav, Gordon Phillips, and Liu Yang. "Private and public merger waves." *The Journal of Finance* 68, no. 5 (2013): 2177-2217.

Matsa, David A. "Competition and product quality in the supermarket industry." *The Quarterly Journal of Economics* 126, no. 3 (2011): 1539-1591.

McKeon, Stephen B. "Employee option exercise and equity issuance motives." *Working Paper* (2015).

McLean, R. David. "Share issuance and cash savings." *Journal of Financial Economics* 99, no. 3 (2011): 693-715.

Megginson, William L., and Kathleen A. Weiss. "Venture capitalist certification in initial public offerings." *The Journal of Finance* 46, no. 3 (1991): 879-903.

Mikkelson, Wayne H., and M. Megan Partch. "Valuation effects of security offerings and the issuance process." *Journal of Financial Economics* 15, no. 1-2 (1986): 31-60.

Mikkelson, Wayne H., and M. Megan Partch. "Withdrawn security offerings." *Journal of Financial and Quantitative Analysis* (1988): 119-133.

Mitchell, Mark L., and Erik Stafford. "Managerial decisions and long-term stock price performance." *The Journal of Business* 73, no. 3 (2000): 287-329.

Myers, Stewart, and Nicholas Majluf. "Corporate financing decisions when firms have investment information that investors do not." *Journal of Financial Economics* 13, no. 2 (1984): 187-221.

Pagano, Marco, Fabio Panetta, and Luigi Zingales. "Why do companies go public? An empirical analysis." *The journal of finance* 53, no. 1 (1998): 27-64.

Park, James L. "Equity Issuance of Distressed Firms: Debt Overhang or Agency Problem?." *Working Paper* (2017).

Pástor, Ľuboš, and Pietro Veronesi. "Rational IPO waves." *The Journal of Finance* 60, no. 4 (2005): 1713-1757.

Ritter, Jay R. "Equilibrium in the initial public offerings market." *Annual Review of Financial Economics* 3, no. 1 (2011): 347-374.

Ritter, Jay R. "The long-run performance of initial public offerings." *The Journal of Finance* 46, no. 1 (1991): 3-27.

Ritter, Jay R., (2020a), SDC (Securities Data Co., or Thomson Financial Securities Data) corrections from Jay R. Ritter of the University of Florida, https://site.warrington.ufl.edu/ritter/files/2019/04/SDC-corrections.pdf

Ritter, Jay R., (2020b), Initial Public Offerings: Updated Statistics on Longrun Returns Cordell Eminent Scholar Warrington College of Business, University of Florida, https://site.warrington.ufl.edu/ritter/files/IPOStatistics2019_Longrun.pdf

Ritter, Jay R., and Donghang Zhang. "Affiliated mutual funds and the allocation of initial public offerings." *Journal of Financial Economics* 86, no. 2 (2007): 337-368.

Ritter, Jay R., and Ivo Welch. "A review of IPO activity, pricing, and allocations." *The Journal of Finance* 57, no. 4 (2002): 1795-1828.

Rock, Kevin. "Why new issues are underpriced." *Journal of Financial Economics* 15, no. 1-2 (1986): 187-212.

Safieddine, Assem, and William J. Wilhelm Jr. "An empirical investigation of short-selling activity prior to seasoned equity offerings." *The Journal of Finance* 51, no. 2 (1996): 729-749.

Shumway, Tyler. "The delisting bias in CRSP data." *The Journal of Finance* 52, no. 1 (1997): 327-340.

Spiegel, Matthew, and Heather Tookes. "Why does an IPO affect rival firms?" *Review of Financial Studies* (2019).

Spiess, D. Katherine, and John Affleck-Graves. "The long-run performance of stock returns following debt offerings." *Journal of Financial Economics* 54, no. 1 (1999): 45-73.

Titman, Sheridan, KC John Wei, and Feixue Xie. "Capital investments and stock returns." *Journal of Financial and Quantitative Analysis* 39, no. 4 (2004): 677-700.

Valta, Philip. "Competition and the cost of debt." *Journal of Financial Economics* 105, no. 3 (2012): 661-682.

Walker, Mark D., and Qingqing Wu. "Equity issues when in distress." *European Financial Management* 25, no. 3 (2019): 489-519.

Willenborg, Michael, Biyu Wu, and Yanhua Sunny Yang. "Issuer operating performance and IPO price formation." *Journal of Accounting Research* 53, no. 5 (2015): 1109-1149.

Zingales, Luigi. "Survival of the fittest or the fattest? Exit and financing in the trucking industry." *The Journal of Finance* 53, no. 3 (1998): 905-938.