COMPETITIVE ADVANTAGES OF GOING PUBLIC: EVIDENCE FROM INCUMBENT FIRMS IN THE USA

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OPEN ACCESS

How to cite this paper: Han, S. (2022). Competitive advantages of going public: Evidence from incumbent firms in the USA. *Corporate Ownership & Control, 19*(3), 42–63. https://doi.org/10.22495/cocv19i3art3

ISSN Online: 1810-3057
ISSN Print: 1727-9232

Received: 21.12.2021
Accepted: 29.03.2022

JEL Classification: G12, G14, G32
DOI: 10.22495/cocv19i3art3

Abstract

Industry incumbent firms (existing public peer firms) experience significant negative stock returns around large initial public offerings (IPO) events in the same industry (Hsu, Reed, & Rocholl, 2010), implying a competitive advantage shift resulting from IPO events. We investigate whether such large IPO events generate real impact in the long run and increase the risk and thus cost of equity of incumbent firms. Using data from 1998–2019, we found that within three years after large IPO events, industry incumbents exhibit positive abnormal returns even after controlling for known asset pricing factors. In addition, their default probability also increases. Using intertemporal capital asset pricing model (ICAPM), we show that incumbent firms' stock returns become more sensitive to economic conditions, in other words, riskier. Following Hou and Robinson (2006), we propose that the increased risk to incumbent firms comes from industry competition. We provide empirical evidence that this is the case. Specifically, firms in industries with low product differentiability, a large number of public firms, and smaller market size have larger increases in expected returns. As robustness tests, we document that industry incumbents exhibit declines in unexpected earnings, which contradicts the notion that the observed positive returns can be attributed to persistent positive cash flow for industry incumbents.

Keywords: IPO, Competition, ICAPM, Industry Incumbent, Profitability, Financial Distress

Authors' individual contribution: The Author is responsible for all the contributions to the paper according to CRediT (Contributor Roles Taxonomy) standards.

Declaration of conflicting interests: The Author declares that there is no conflict of interest.

Acknowledgements: We would like to express our great appreciation to faculty members in the University of Georgia Finance Department for all the guidance and advice they generously gave us. We would also like to thank all the attendees during our FMA 2015 presentation for the constructive comments they shared with us.

1. INTRODUCTION

Going public is one of the most important and complex decisions that a firm can make. However, the determinants of firms' initial public offerings (IPO) decisions are still not fully understood from an academic perspective. Pagano, Panetta, and Zingales (1998) recommend assessing this problem not only from *ex-ante* characteristics of the firms but also from *ex-post* consequences of such decisions[1]. In practice, the extensive literature mainly focuses on the *ex-post* impacts of firms' listing decisions to investigate firms' motivations for going public, as studies on firms' *ex-ante* incentives to go public are largely constrained by limited access to data from private firms.

[1] *Ex-post* effects can complement the evidence inferred from *ex-ante* characteristics for two reasons. First, some motivations can only be assessed by looking at *ex-post* data. Second, some effects may not be fully anticipated and can only be uncovered by using *ex-post* data.

While earlier studies offer insights into the going-public decision from the perspective of the capital market[2], recent research increasingly emphasizes the product market competitive advantages associated with going public. These studies suggest that going public sends positive signals to the public regarding issuing firms' own quality and their product quality (Stoughton, Wong, & Zechner, 2001; Hsu, Reed, & Rocholl, 2010); provides first-mover advantages (Spiegel & Tookes, 2008; Maksimovic & Pichler, 2001); and helps firms engage in more aggressive and riskier strategic activities such as R&D (Chod & Lyandres, 2011). Moreover, capital collected through IPOs helps facilitate a firm's investment or its mergers and acquisitions (Brau & Fawcett, 2006; Celikyurt, Sevilir, & Shivdasani, 2010) and enables firms to acquire related patents (Bernstein, 2015). As to whether this public channel has a real impact on the product market, Chemmanur, He, and Nandy (2010) and Chemmanur and He (2011) provide direct empirical evidence that listing firms experience increases in their market shares after IPOs, while the market shares of industry incumbents (i.e., existing firms in the same industry) decrease. However, these studies pay attention only to IPO-related product market advantages for issuing firms. Since IPO firms are on average much smaller than incumbent firms, it is still unclear whether these IPOs can actually impact industry incumbents.

Some recent studies (Akhigbe, Borde, & Whyte, 2003; Hsu et al., 2010; McGilvery, Faff, & Pathan, 2012; Li, Sun, & Tian, 2018) examine incumbents' stock price reaction to IPO events in order to infer the existence of IPO-related competitive effects on industry incumbents but find mixed results. Hsu et al. (2010) and McGilvery et al. (2012) find negative valuation effects for industry incumbents around large IPO events and imply that the market expects lower future cash flows for industry incumbents after such events. However, it is unknown whether the negative valuation effects result only from the negative cash flow effect or are also related to the increase in risk. The current study investigates this unexplored risk effect of IPOs, specifically, whether IPOs increase industry incumbents' risk and thus cost of equity. We provide empirical evidence that large IPO events alter the cost of equity of industry incumbents in the long run and report that the increased risk premia are associated with intensified competitive pressure and higher default risk.

Specifically, we document first that incumbent firms exhibit positive abnormal returns during the 3–5-year post-listing period after controlling for existing factors[3], and their abnormal returns co-vary positively with macroeconomic conditions. Compared with the 3–5-year period before IPOs, industry incumbents experience an increase in abnormal returns ranging from 0.2–0.3% monthly (around 3% per year). Moreover, the co-variation of industry incumbent firms' returns with macroeconomic conditions ("beta") also increases subsequent to large IPO events. This suggests that an increase in returns is likely to be associated with increased economic risk.

As to through which channel IPO events increase the risk for industry incumbents and what kind of risk increases, we speculate that IPOs change the product market structure within the industry (Chemmanur et al., 2010; Chemmanur & He, 2011), which has risk implications that are priced in stock returns (Hou & Robinson, 2006). In particular, IPO events intensify the competition within the industry[4] and impose more threats to industry incumbents, thus increasing incumbent firms' default risk and their cost of equity. Using the default probability measure of Campbell, Hilscher, and Szilagyi (2008), we document that industry incumbents face a significantly higher probability of default after large listing events in their industries.

Cross-sectionally, we find that incumbent firms operating in industries where IPOs are associated with more competitive advantages have higher expected returns subsequently, supporting the speculation that enhanced competition risk accounts for higher abnormal returns observed for incumbents after IPO. We find that IPOs' effect on incumbent firms is stronger in more competitive industries, that is, industries with higher levels of product substitutions, a larger number of firms, and a smaller market size[5].

The findings of the present study provide new empirical evidence in the discussion of IPO-related advantages. Based on the average market capitalization of industry incumbents in our sample (US$3,572 million), a 3% increase in returns can translate into more than a US$100 million increase in the cost of equity each year. Knowledge with regard to this long-term impact on the cost of capital has implications for both investors and incumbent firms. As listing firms only account for a small portion of the stock market[6], it is beneficial for investors to know the valuation effects of listing events on incumbent firms so that they can adjust their allocation more efficiently. Moreover, IPO firms and private firms considering public offerings could learn from this paper the market opinion regarding their decision to go public and, more critically, the real consequences of listing on their competitors. Last but not least, our findings will help industry incumbent firms to better understand what competitive advantages accrue to the issuing firms so that they can adjust their decisions about operations to respond in an optimal manner.

The rest of the paper is structured as follows. Section 2 reviews the previous literature and develops the research hypotheses. Section 3 provides the research methodology, sample, and data. Section 4 presents the empirical results of the research. Section 5 provides the robustness test. Section 6 concludes the paper.

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[2] These works include but are not limited to studies on enhancing liquidity (Amihud & Mendelson, 1986), reducing information asymmetry (Benveniste & Spindt, 1989), diversifying owner risk (Chemmanur & Fulghieri, 1999; Mikkelson, Partch, & Shah, 1997), improving public monitoring (Holmström & Tirole, 1993), and helping early-stage investors exit.

[3] Abnormal returns do not conflict with market efficiency in the sense that positive abnormal returns reflect additional risk not captured by existing factors. In the current context, abnormal returns do not imply the market is inefficient. If the market is inefficient, we should observe either that the negative reaction continues after the IPO date (under-reaction) or that subsequent positive returns have similar magnitude as the negative returns around IPO dates (overreaction). Instead, we observe positive returns subsequent to IPOs which are much larger in magnitude.

[4] Spiegel and Tookes (2020) construct a model in which industry becomes more homogeneous in the product environment and customers are more likely to switch between firms after IPOs.

[5] According to Karuna (2007), competition is multi-dimensional instead of the single dimension captured by the Herfindahl index. Specifically, controlling for industry concentration (Herfindahl index), high price substitutability, large firm number, and larger market size all capture greater competition in different dimensions. We discuss this in more detail in subsection 4.6.

[6] Using a similar sample, Hsu et al. (2010) show that existing publicly traded firms (industry incumbents) comprise 97.5% of the total post-IPO market capitalization of industries in which IPO occurs. In contrast, IPO firms comprise the remaining 2.5% of industry portfolio value.

2. PREVIOUS LITERATURE AND HYPOTHESES DEVELOPMENT

The existing literature features several theories regarding the drivers and impacts of IPO activities. Fundamentally, IPOs involve extensive information disclosure and sales of firm shares to public investors, which increase liquidity and reduce information asymmetry. Once newly listed firms obtain capital, they can reduce leverage (Eckbo & Norli, 2005; Armstrong, Foster, & Taylor, 2015), enjoy greater investment flexibility (Lang, Ofek, & Stulz, 1996; Zingales, 1998), and pursue new projects and growth opportunities (Chevalier, 1995; Phillips, 1995). Further, collected capital can fuel innovations and acquisitions. Spiegel and Tookes (2008) construct a model in which firms in the same industry compete for market share and show that firms go public to finance their innovations. Similarly, Chod and Lyandres (2011) argue that going public facilitates firms' investment in riskier projects, such as R&D, by helping to diversify the idiosyncratic risk for owners of the firm. Booth and Chua (1996) and Celikyurt et al. (2010) show that going public facilitates acquisitions, and newly listed firms outpace incumbents in terms of acquisition activities. Bernstein (2015) also documents that going public increases issuing firms' acquisitions of external innovations. Aghamolla and Thakor (2021) find that in the drug development industry, the private competitors of recent IPO firms are more likely to go public, implying that IPOs could bring competitive advantages to firms going public.

In addition to the product market advantages mentioned above, IPOs can also serve as a positive signal of the quality of the issuing firm and its product. Chemmanur and Fulghieri (1999) show that highly ranked investment banks can play an important role in certifying firm value. IPOs underwritten by prestigious investment banks are associated with lower risk and better long-term operating performance (Carter & Manaster, 1990; Carter, Dark, & Singh, 1998). Stoughton et al. (2001) establish a model in which stock prices contain information about product quality. The model predicts that only good-quality firms go public. Given that IPOs serve as positive signals for the IPO firms, theoretical works by Maksimovic and Pichler (2001) and Spiegel and Tookes (2008) suggest that IPO firms' market share should increase in the years subsequent to IPOs. Chod and Lyandres (2011), Chemmanur et al. (2010) and Chemmanur and He (2011) find consistent empirical evidence that newly listed firms experience increases in their market shares after IPOs[7].

Since industry incumbent firms and IPO firms share the same industry environment and compete with each other, the existence of a competitive shift between them (i.e., more market share for IPO firms) bears negative implications for industry incumbents (Kim, Lacina, & Park, 2008). Intuitively, if IPOs help issue firms gain advantages (i.e., positive news); IPOs should also incorporate negative news for industry incumbents. Three recent studies directly examine the short-term valuation effects of IPO events on industry incumbents, or in other words, how incumbent firms' stock prices react to IPOs within the same industry[8]. Akhigbe et al. (2003) find an insignificant short-term valuation effect. In contrast, Hsu et al. (2010) and McGilvery et al. (2012) focus only on large listing events and find a significant negative valuation effect around the announcement and listing dates of large IPO events[9].

One possible explanation for the discrepancy in their results is the differences between their samples. Akhigbe et al. (2003) study the average effects of all IPOs, while Hsu et al. (2010) and McGilvery et al. (2012) only focus on large IPO events. Since new issuing firms are much smaller than existing incumbents on average, the competitive impacts they generate could be rather limited[10]. Thus, including small IPO events in the sample may contaminate the valuation effects of large IPO events and lead to insignificant average valuation effects. The discrepancy of these results also indicates that there are cross-sectional differences in IPOs' effect on industry incumbents. Given the findings from Hsu et al. (2010) and McGilvery et al. (2012) that only large IPOs have greater competitive impacts, we focus on large IPO events for the current paper.

If large IPO events in our sample provide issuing firms with competitive advantages, successful completion of these IPOs should be perceived as negative news for industry incumbents and thus generate a negative valuation effect on incumbent firms' stock prices[11]. Since we apply different filtering criteria and cover a different sample period[12], we feel it is important to confirm that the IPO-related valuation effect exists for our sample before we further evaluate the long-term impact of IPO events on long-term stock returns. The first hypothesis is proposed as follows:

H1: Incumbent firms' stocks experience negative returns around large IPO events in the same industry.

The presence of a negative valuation effect on industry incumbents suggests that a large IPO implies either decreased future expected cash flow or increased risk (discount rate) or both for the incumbents. Hsu et al. (2010) document that compared with pre-IPO periods, incumbent firms' operating performance and profitability decline within four years subsequent to IPO events, implying that industry incumbents experience declining cash flows after large IPO events. As the sample in this study is different from that of Hsu et al. (2010), we posit the second hypothesis for our sample:

[7] There is a great deal of empirical evidence showing that IPO firms have declining profitability and efficiency after IPOs, which seems to contradict evidence about increasing market share for issuing firms post listing. Clementi (2002) argues theoretically that IPOs can increase the issuing firm's operating scale, which contributes to declining profitability and productivity. Chemmanur et al. (2010) document that while productivity and sales growth decline after firms go public, their sales, capital expenditure, total employment, and so forth keep increasing over the years before and after public listing.

[8] From a methodological perspective, some studies have examined the intra-industrial effect of certain corporate events. For example, Lang and Stulz (1992) study the effect of bankruptcy announcement on industry rivals and distinguish between competitive effects and contagion. Kim et al. (2008) study the effects of earnings announcements on industry rivals and document negative information transfer due to competitive shifts.

[9] Li, Sun, and Tian (2018) find negative valuation effect for IPO of banks in China. However, since their study only focuses on the banking industry in China, it lacks generalizability.

[10] It is likely that negative signals embedded in small IPOs are smaller in magnitude and easily offset by positive signals regarding growth perspective, leading to overall unobservable valuation effects.

[11] Hsu et al. (2010) argue that both the filing dates and listing dates have information content as there is still a lot of uncertainty in the market when IPOs are filed. Completion of these IPOs solves this uncertainty and thus has new information embedded in the listing dates, too.

[12] IPO firms in our samples are only 50–75% as big (in terms of market capitalization, sales, and/or assets) as IPO firms in Hsu et al. (2010).

H2: Incumbent firms' operating performance declines following large listing events in the same industry.

The existence of negative valuation effects on industry incumbents raises the question of whether, in addition to information about expected future cash flows, IPOs also convey information related to the risk and thus cost of equity for their industry incumbents. The answer is likely "yes". Hou and Robinson (2006) show empirically that product market structure has risk implications that are priced but not captured by market risk premium, size, value, and momentum factors. Hou and Robinson (2006) argue that firms in competitive industries confront higher default risk and invest more in innovation activities (higher innovation risk) than firms in concentrated industries. Investors care about these additional risks and require higher returns as compensation, generating higher risk premia for firms in competitive industries. Since an IPO could change the product market structure, it then changes risk within the industry. As newly listed firms gain market shares from industry incumbents, they pose credible threats to industry incumbents, which in turn increase incumbent firms' distress risk. Moreover, industry incumbents are likely to change their operating strategies in response to the intensified competition. For example, they may increase their R&D investment, which increases their innovation risk. These enhanced risks predict increased abnormal returns for industry incumbents during the post-issuance era. We propose the third hypothesis:

H3: Stocks of incumbent firms exhibit positive abnormal returns subsequent to large listing events with CAPM and Fama-French (3, 4, and 5) factor models.

To further investigate whether post-IPO abnormal returns are consistent with a risk-based explanation, we examine the time-series properties of incumbents' abnormal returns. Specifically, we apply the intertemporal capital asset pricing model (ICAPM) and examine how incumbent firms' returns vary with macroeconomic conditions. In the ICAPM framework, risk means lower returns during bad times, which transfers wealth from bad times to good times and is undesirable for investors. We use the innovation terms of the inflation rate, term premium, default premium, dividend yield, and T-bill rates as proxies for expected future economic conditions, as they are known to be closely related to macroeconomic conditions and are very persistent. If incumbent firms' positive abnormal returns originate from risks, we expect that stock returns of incumbent firms exhibit a pro-cyclical feature. This means that stocks of incumbent firms should exhibit lower returns during recession periods, but higher returns during expansion periods. We present the following hypotheses:

H4a: Stock returns of industry incumbents co-vary positively with macroeconomic conditions.

In addition, if incumbent firms' abnormal returns are the result of increased risk caused by enhanced competition from newly listed firms, using the ICAPM framework, we should observe that incumbent firms' stocks become more pro-cyclical after large IPO events (higher risk) compared to the pre-IPO period. Thus:

H4b: Stock returns of industry incumbents co-vary more with macroeconomic conditions during post-issuance periods.

According to Hou and Robinson (2006), increased competition risk in the industry is associated with higher default probabilities for firms in the industry. If large IPOs increase competition risk in the industry, industry incumbents ultimately should also have increased default probability after such events. We propose the fifth hypothesis:

H5: Incumbent firms have a higher default probability after large IPO events.

If increased returns are attributable to the competitive advantages shifting to newly listed firms after IPO events, cross-sectional IPO events that can exert more competitive impacts on incumbent firms should be accompanied by even higher abnormal returns for industry incumbents subsequent to such listing events. It is possible that industry concentration is related to the impact of such competitive effects from IPO events. However, it is unclear whether industry concentration strengthens or weakens such competitive effects. For example, on the one hand, monopolistic firms in highly concentrated industries have more market power and can employ tactics such as price increases to drive out competitors, so competitive impacts might be quite limited. On the other hand, such monopolistic firms could be lacking experience in fair market competition, and if this is the case, such competitive effects from large IPO events can potentially make a big difference[13]. Therefore, whether industry concentration strengthens or weakens such competitive effect is an empirical question. We propose the following hypotheses:

H6a: Industry concentration affects the cross-sectional variation in incumbent firms' long-term stock returns[14].

Karuma (2007) argues that industry competition is multi-dimensional rather than the single dimension captured by industry concentration and that several industry characteristics are related to competition after controlling industry concentration. Specifically, a higher degree of product similarity (lower differentiability), smaller market size, and lower barrier to entry (entry cost) all indicate intense competition conditional on industry concentration[15]. Each of these measures captures a piece of the relative competitiveness of each industry and thus can be used to measure variation in the level of competition across different industries. In industries where competition is more intense, additional competitive advantages can impose bigger threats for existing incumbent firms, whose risk will increase more as a result. Following Karuna (2007), we measure product market competition with a level of product substitutability, market size, entry cost, and a number of public firms in the industry, and examine how these measures relate to the long-term stock returns of industry incumbents[16] using the following hypotheses:

[13] Previous studies that investigated the industrial effects of corporate events provide evidence for both situations. Hoberg and Phillips (2010) show that the negative spillover effect is more severe in competitive industries. In contrast, Sarkissian and Wang (2014) show that the negative impact of foreign IPOs is more severe for concentrated industries.
[14] As pointed out above, the prediction regarding how industry concentration affects incumbent firms' ability to response to the threats of new listed firms is ambiguous, so the hypothesis here is non-directional.
[15] Specifically, Karuna (2007) and others (e.g.,Raith, 2003) argue that industry concentration is endogenously determined by market fundamentals such as substitutability of product, market size, or firms' cost to enter the market. Concentration could indicate either intense competition or low competition.
[16] More details are included in subsection 4.6.

H6b: Given industry concentration, the degree of product similarity correlates positively with incumbent firms' long-term stock returns.

H6c: Given industry concentration, the number of public firms correlates positively with incumbent firms' long-term stock returns.

H6d: Given industry concentration, market size correlates positively with incumbent firms' long-term stock returns.

H6e: Given industry concentration, the barrier to entry is negatively associated with incumbent firms' long-term stock returns.

3. RESEARCH METHODOLOGY, SAMPLE, AND DATA

We focus on the risk implication of IPO events on industry incumbents and thus the impact of IPO events on incumbents' cost of equity. We choose realized returns over implied cost of capital (ICC) as our measure of the cost of capital. Previous studies argue that *ex-post* realized returns could be a noisy proxy of *ex-ante* expected returns (Fama & French, 1997, 2002; Pastor, Sinha, & Swaminathan, 2008), and recent finance and accounting studies have developed several measures of implied cost of capital to better capture *ex-ante* expected returns (Gebhardt, Lee, & Swaminathan, 2001; Hou, van Dijk, & Zhang, 2012). However, we choose realized returns in the current context for several reasons. First, to estimate ICC, either analyst forecasts of future cash flows or certain earnings forecast models need to be employed to estimate future cash flow to equity holders. Using analyst forecasts will lose roughly 40% of the sample firms (Hou et al., 2012) while using earnings forecast models involves many assumptions as well as issues of model misspecification. Second, Larocque and Lyle (2017) proved that for many occasions, ICCs are not associated with future ROE. This means that ICCs cannot forecast future stock returns and can hardly serve better than realized returns as proxies for expected returns. Last, as the current study looks at the impact of large IPO events on incumbent firms, using realized returns better captures the actual costs for incumbent firms. We will explain the methodology for our ICAPM framework as well as the default probability function and all other cross-sectional tests in Section 4 together with the empirical results.

We obtain our initial IPO sample from the Securities Data Company (SDC) New Issue database, which consists of 2789 completed US industrial IPOs over the sample period from 1998 to 2019[17]. To minimize the effect of data errors on our results, we correct for mistakes in SDC's database following Jay Ritter's "Correction to Security Data Company's IPO database"[18]. We exclude from the sample unit offerings, foreign issues, REITs, closed-end funds, reverse LBOs, spin-offs, and ADRs. Accounting information for the IPO sample firms comes from the Compustat database and stock market information from the CRSP database. Since our analysis requests clear identification of the industry, we require the SIC codes of issuing firms from Compustat, CRSP, and/or prospectuses retrieved from SEC Edgar Online. The filtered sample includes 2424 IPO events with information available and identified Fama-French 49 industry from 1998 to 2019.

We constrain the current study to large IPO events for the reasons stated in Section 2. To select the most influential IPOs and purge the contamination of small IPO events, we follow the method used in Hsu et al. (2010) and McGilvery et al. (2012). Specifically, we use the most recent sales data available prior to going public (usually one year prior) as a measure of size. When sales are not available for the year before the IPO, we estimate it by using sales in the year of the IPO, adjusted by industry sales growth[19]. A total of 1981 IPO events have sales data on Compustat and CRSP either for one year before the IPO or for the IPO year. We define and select large IPO event firms as those that have the largest sales during the surrounding seven-year window (three years before and after IPOs). The final IPO sample comprises 192 IPO events.

The advantage of this sample selection is that it makes good use of available data. The 7-year window can clearly distinguish post-IPO periods from pre-IPO periods and help purge the contamination from small IPO events better[20]. However, filtering criteria so stringently makes the sample less representative and limits the generalizability of results. The present study weighs the pros and cons and adapts alternative filtering processes that are less exclusive while still attempting to weed out the noise associated with confounding small IPOs. We repeat our tests for several alternative samples with many more observations[21]. The results using these different samples are qualitatively similar and are discussed briefly in the section on robustness tests below.

We identify industry incumbents as existing public firms primarily operating in the same Fama-French 49 industry as the IPO event firms. Incumbent firms must be publicly tradable at least three years before the IPO event year so that we can get sufficient pre-IPO data to make reliable comparisons with post-IPO periods. Accounting information and stock returns of industry incumbents need to be available from Compustat and CRSP. We impose no requirement on either the listing exchanges of incumbents or how many years they survive after corresponding IPO events, as these requirements are likely to generate survivorship bias. The final incumbent firm sample includes 7072 IPO event-firm observations covering 3815 unique incumbent firms.

Table 1 reports the descriptive statistics for the universe of IPO firms that have data available from CRSP and Compustat, the sample of large IPO events, as well as the sample of industry incumbents. Market capitalization, sales, and assets

[17] In 1997, SFAS 131 replaced SFAS 14 and firms changed their segment reporting. Since we use Compustat Segment files to calculate measures related to industry competition, our sample period starts from 1998 to maintain consistency. Our sample ends in 2019 as another 3–5 years of data are needed to examine the long-term effects of IPO events.

[18] Available online at http://bear.cba.ufl.edu/ritter/ipodata.htm

[19] We calculate the sales growth for all the IPO firms during that year for each industry first, and then divide sales for the IPO year (year 0) with 1 + sales growth rate from year -1 to year 0.

[20] It might involve some look-ahead bias, but the results are qualitatively similar even when we use other sample selection criteria, such as IPO firms with pre-IPO sales in the top 10% among all IPO firms in the same industry in the same year.

[21] Results from different samples suggest that the more firms that are included in the sample and the smaller the IPO event firms are, the less strong the results are. This confirms that it is necessary to restrain the sample to large IPO event firms when analyzing the competitive impacts of such events on industry incumbents. Similarly, Park, Song, and Niu (2018) document that only large (not small or medium sized) banks increase their profitability after going public.

of IPO firms are measured using the first available data points from CRSP or Compustat, while market capitalization of incumbents is measured at the end of the large IPO event month. Table 1 shows that issuing firms are on average much smaller (even after going public) than existing firms: industry incumbents are about 10 times larger in terms of sales ($401.71 million vs. $3,880.98 million) and total assets ($527.23 million vs. $4,266.7 million). However, the first two columns of Table 1 also show that the sizes of IPO firms are positively skewed. This suggests that while IPO firms are much smaller than industry incumbents on average, there are some large firms going public.

Table 1. Descriptive statistics

	IPO_all		*IPO_smpl*		*Incumbents*		*Differences*
	Obs = 1981		*Obs = 192*		*Obs = 7072*		*Wilcoxon z-test*
	mean	*median*	*mean*	*median*	*mean*	*median*	*p-value*
Assets ($ mil)	527.23	124.36	4,037.29	781.62	4,266.70	421.50	0.004
Sales ($ mil)	401.71	56.86	4,099.24	730.21	3,880.98	434.67	0.001
Market capitalization ($ mil)	821.37	391.42	1,470.57	702.58	3,572.57	346.72	0.002
Venture backed	0.67	1	0.17	0			

Notes: The table reports the descriptive statistics for the three samples of IPO event firms and industry incumbent firms. All variables are measured at the end of the IPO event year. Accounting information data come from Compustat annual files and stock market data come from CRSP. The unfiltered sample includes 1981 IPO events that have data available from CRSP and Compustat. We select 192 large IPO events based on their pre-IPO sales. Incumbent firms are defined as firms that are operating in the same Fama-French 49 industry as the IPO firms and are publicly traded for at least three years before the IPO year. The last column documents the p-value from the Wilcoxon z-test of equal rank between IPO sample firms and the sample of industry incumbents.

Selected IPO event firms are much larger than the average IPO firms. They have significantly greater sales (US$730.21 million vs. US$434.67 million) and assets (US$781.62 million vs. US$421.50 million) when compared with industry incumbents using a Wilcoxon Z test. This is consistent with previously documented results in Hsu et al. (2010) that the average IPO firm is much smaller than existing incumbents and their competitive effects are very limited. Large IPO firms are more capable of exerting meaningful competitive pressure on industry incumbents.

4. EMPIRICAL RESULTS

4.1. Negative valuation effect around IPO events (*H1*)

Since IPO firms and incumbents share the same market environment, if large firms could gain additional competitive advantages through IPOs, such IPO events should contain negative information for incumbent firms. Consequently, the market should react negatively to incumbent firms' stocks around IPO event dates, and there should be a negative valuation effect. We replicate the finding of short-term negative valuation effect for incumbents documented in Hsu et al. (2010) in Table 2. Specifically, we calculate cumulative abnormal returns of incumbent firms around large IPOs in the industry using CAPM, the Fama-French 3-, 4-, and 5-factor model (including profitability and investment factors). The model estimation window begins 255 days and ends 42 days prior to the IPO dates. We require incumbent firms to have at least 50 daily observations during the window in order to reasonably estimate model parameters.

Table 2 shows that stock prices of incumbent firms drop significantly around large IPO events in the same industry. Cumulative abnormal return (CAR) across various event windows is almost always significantly negative. CAR in the three-day window around the listing date is a statistically significant -0.13% (-0.19%, -0.16%, -0.14%) with the CAPM (Fama-French 3-, 4-, 5-factor model). When extending backwards, CARs starting five days before the IPO until one day after are significant at -0.11% (-0.12%, -0.13%, -0.12%) with the CAPM (Fama-French 3-, 4-, 5-factor model). When extending the window further backward to include 10–20 days prior to the listing date, we still observe negative significant returns. This suggests that the stock price of industry incumbents begins to adjust before the actual IPO date, consistent with the observation that the market can predict the success of the deal before the actual listing dates (Hsu et al., 2010)[22].

When the event windows extend to cover 10–20 days after the IPOs, we see the stock prices of industry incumbents continue to drop. CARs become -1.01% (-0.53%, -0.47%, -0.44%) during the 21 days around IPO dates, close to monthly return between -0.44% and -1.01%, which is economically significant. This indicates that the negative stock response persists for a relatively long time after IPOs. In the untabulated results, we calculate the CARs around IPO filing dates rather than listing dates. The results are similar and show that the stock prices of industry incumbents fall significantly around the IPO file dates. The magnitudes of negative CARs across various event windows are similar to those documented by Hsu et al. (2010).

Overall, the results in Table 2 indicate that incumbent firms experience a significant drop in their stock prices when a large firm in the same industry files for IPO and later goes public, consistent with *H1*. Price declines persist for several days (at least 20 days as shown in the table) after the event dates. This implies that the market on average perceives successful large IPO events as bad news for industry incumbents. We explore in detail whether this negative valuation effect comes from unexpected negative cash flow shocks or increases in the risk of industry incumbents (or both) in the next section.

[22] We also examine the CARs of incumbent firms using two-digit SIC industry definition, three-digit SIC industry definition and Fama-French 49 industry definition and find they are quite similar in magnitude. All the returns are significant at the 1% level across the assorted event windows. All results are qualitatively similar.

Table 2. Cumulative abnormal returns of incumbent firms around IPO dates

Event window	*CAPM*		*Fama-French 3-factor*		*Fama-French 4-factor*		*Fama-French 5-factor*	
	CAR	*t-stat*	*CAR*	*t-stat*	*CAR*	*t-stat*	*CAR*	*t-stat*
(-1, +1)	-0.13%	-1.81	-0.19%	-2.71	-0.16%	-2.35	-0.14%	-2.27
(-5, +1)	-0.11%	-1.76	-0.12%	-2.28	-0.13%	-2.09	-0.12%	-2.17
(-5, +5)	-0.13%	-2.01	-0.11%	-1.81	-0.08%	1.01	-0.09%	1.23
(-10, +1)	-0.52%	-3.47	-0.38%	-2.68	-0.35%	-2.31	-0.37%	-2.19
(-10, +5)	-0.57%	-3.79	-0.37%	-2.31	-0.23%	-2.01	-0.21%	-1.99
(-10, +8)	-0.79%	-4.11	-0.51%	-2.57	-0.35%	-1.78	-0.31%	-1.69
(-10, +10)	-1.01%	-5.15	-0.53%	-2.81	-0.47%	-2.19	-0.44%	-2.07
(-15, +10)	-1.22%	-5.12	-0.69%	-3.21	-0.54%	-2.31	-0.53%	-2.27
(-20, +10)	-1.19%	-4.77	-0.72%	-3.09	-0.52%	-2.04	-0.49%	-2.01
(-10, +15)	-1.13%	-4.75	-0.53%	-2.36	-0.29%	-1.93	-0.27%	-1.97
(-10, +20)	-1.46%	-5.79	-0.61%	-2.57	-0.24%	-1.91	-0.22%	-1.81

Notes: The table reports the cumulative abnormal returns of incumbent firms around IPO filing dates and initial trading dates. Competitor firms have to be in the same industry as the IPO firms and public at least three years before the IPO year with available data. Abnormal returns are calculated using market-adjusted excess return, the Fama-French 3-, 4-, and 5-factor model including the operating profitability and investment factors, which is the difference between actual stock return and the expected model stock return. Four models are estimated using an estimation window between 255 days and 42 days prior to the IPO events. We require the incumbent firms to have at least 50 daily observations during the estimation windows to achieve reasonable parameter estimations. Various event windows are applied.

4.2. Long-term operating performance (*H2*)

To investigate whether the short-term valuation effect originates from investors' expectations about future cash flow declines for industry incumbents due to intensified competition, we examine how incumbents' operating performance changes over time. Table 3, Panel A reports the univariate changes of incumbent firms in their operating performance, KZ financial constraint index (Kaplan & Zingales, 1997), and Altman Z-score after large IPO events in the same industry: incumbent firms not only exhibit reduced sales growth and asset growth but also experience increases in their KZ index and decreases in Altman Z-score. This indicates that incumbents have reduced operating performance and face more financial constraints subsequent to IPO events than before, consistent with *H2*.

We study further how incumbent firms' operating performance changes after IPO events in the industry, controlling for related factors that are known to affect performance. Specifically, we estimate the following model in which performance is a function of firm size, valuation, and past performance:

$$Performance_{i,t} = \alpha + \beta * IPO_{i,t} + \gamma * Controls_{i,t} + \epsilon_i + \theta_t + \varepsilon_{i,t} \quad (1)$$

where, $Performance_{i,t}$ is measured as sales growth, operating income growth, and investment growth (capital expenditure) in each year t for every incumbent firm i; and $IPO_{i,t}$ is an indicator variable that equals 1 if year t is within the 3 years subsequent to a sample IPO event in firm i's industry, and 0 otherwise. Equation (1) is estimated for incumbent firms that have data from both pre-IPO years and post-IPO years. We include industry and year-fixed effects to control for unobserved heterogeneity. The estimated coefficient of IPO measures how much the IPO event contributes to the decline of incumbent firms' operating performance.

Table 3. The effect of IPO events on operating performance of industry incumbent firms

Panel A: Changes of financial constraints for incumbents over time				
mean	***Sales growth***	***Asset growth***	***KZ index***	***Altman Z-score***
three years before the IPO	18.79%	15.26%	0.067	4.76
three years after the IPO	10.98%	11.21%	0.149	2.79
t-stat	-7.69	-5.37	5.76	-10.98
median	***Sales growth***	***Asset growth***	***KZ index***	***Altman Z-score***
three years before the IPO	9.55%	8.31%	0.303	3.70
three years after the IPO	6.10%	5.69%	0.350	3.23
Wilcoxon Z test	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Panel B: Estimated panel regression of performance on IPO dummy				
	Sales growth	***Operating income growth***	***Capital expenditure growth***	***R&D intensity***
IPO dummy	-0.095	-0.132	-0.129	0.157
	(-21.79)	(-12.11)	(-11.79)	(4.69)
Lag dependent variable	-0.091	-0.271	-0.267	0.378
	(-15.13)	(-32.79)	(-40.32)	(39.98)
Assets	0.149	0.096	0.301	-0.217
	(25.79)	(6.69)	(20.85)	(-4.95)
M/B	0.009	0.019	0.012	-0.013
	(15.31)	(12.29)	(8.31)	(-3.12)
Industry fixed effect	Yes			
Year fixed effect	Yes			
Clustered std. error	Yes			
N	27,143	27,143	27,891	17,895
Adj. R^2	0.3151	0.2957	0.2179	0.7017

Notes: The table documents how operating performance changes over time for industry incumbents. Panel A reports how the KZ index and Altman Z-score change for industry incumbents over time. Data used to calculate the KZ index and Altman Z-score come from Compustat. T-statistics and Wilcoxon test statistics are reported. Panel B reports the estimates from a panel regression of incumbent firms' sales growth, operating income growth, and capital expenditure growth on an IPO indicator, controlling for firm age, size, valuation, past performance, industry and year fixed effects. Sales growth is the difference between current log sales and previous year log sales. Operating income growth is the difference between the log current operating income and log previous year income. Capital expenditure growth is the difference between log current capital expenditure and log one-year-prior capital expenditure. R&D intensity is measured as R&D scaled by sales. IPO dummy is an indicator variable that equals 1 if year t is within 3 years after sample IPO events, and 0 otherwise. M/B is the market-to-book ratio. Standard errors are clustered at the firm level. T-statistics are reported in parentheses.

Table 3, Panel B presents the estimated results of Equation (1). As shown in Panel B, sales growth for incumbent firms is significantly related to size and valuation. Estimated coefficients for the IPO indicator are negative and significant across all performance measures: the sales growth of incumbent firms declines by nearly 10%, operating income growth slows down by 13.2% and capital expenditure declines by 12.9% after large IPO events in the industry, consistent with *H2*. Further, the last column of Panel B shows that R&D intensity (R&D/sales) increases by about 15.7% after large IPO events. This result implies that incumbent firms do not cut their R&D investment following reduced sales; rather, incumbent firms increase their R&D proportionally to make themselves more competitive with newly listed firms. This is consistent with Hsu et al.'s (2010) finding that incumbent firms with higher R&D intensity perform better subsequent to large IPO events and with Hou and Robison's (2006) argument that greater competition usually makes firms invest more in innovation. Last, according to Hou and Robinson (2006), such an increase in R&D intensity also implies that innovation risk is likely to increase after large IPO events in the same industry, and consequently so do incumbent firms' long-term stock returns.

4.3. Long-term stock performance (*H3*)

In this section, we examine the long-run stock performance of incumbent firms post-listing to assess the impact of IPO on industry incumbents. Specifically, we apply the calendar-time portfolio approach. Fama (1998) and Mitchell and Strafford (2001) recommend a monthly calendar-time portfolio approach for measuring long-term abnormal performance for three reasons. First, the cross-correlations of firm abnormal returns are automatically accounted for in the portfolio variance. Second, the monthly returns of portfolios are less susceptible to problems in the model. Last, the distribution of the estimator is better approximated by the normal distribution, allowing for more powerful statistical inference.

Following previous studies on post-IPO underperformance, we create both IPO-firm portfolios and incumbent-firm portfolios to measure the stock performance of IPO and incumbent firms within three years subsequent to IPO events, respectively. Specifically, monthly returns for a specific company are included in the IPO portfolio for that calendar month, if the company went public within the past 36 months [-37, -1][23]. Returns for incumbent firms are included in the incumbent portfolio if IPOs happened in the same industry within the past 36 months [-37,-1]. Table 4 reports returns for these calendar-time portfolios. T-statistics are corrected using Newey-West with 5 lags of autocorrelation for past returns.

As shown in Table 4, long-term returns for IPO sample firms are always negative across different models. After controlling for existing factors, the monthly alphas for IPO firms range from -0.279% to -0.176%. This is consistent with extensive previous literature documenting IPO firms' underperformance within 3 to 5 years after they are publicly listed. None of these negative returns is significant for our sample, which is also consistent with previous empirical studies documenting that the scale of IPO underperformance declines with the size of the listing firm (Ritter, 1991; Loughran & Ritter, 1995), meaning as the size of the listing firm increased greatly, the underperformance became much less severe. The observed insignificant negative returns could be reasonably explained by the large size of the IPO event firms included in our sample. As evident from the descriptive statistics included in Table 1, the average market capitalization of IPO event firms included in our sample is US$1,470.57 million (median US$702.58 million), almost twice as large as the universe of all IPO firms (mean US$821.37 million, median US$391.42 million).

Table 4 also shows that alphas for corresponding incumbent firm samples are always positive and significant at 1% even after controlling for market risk, size, value, momentum, profitability, and investment factors. Abnormal returns for incumbent firms range from 0.531% with the Fama-French 5-factor model to 0.880% with CAPM. The differences of abnormal returns between IPO portfolio and incumbent portfolio are always significant, ranging from -0.093% to −1.137% monthly, and are roughly over 10% annually.

The differences in alphas suggest that either incumbent firms have different risk exposure from IPO firms, or investors have difficulty valuing incumbent firms, contributing to their positive abnormal returns. The latter explanation seems less plausible, as industry incumbents exist in the public market for a much longer time than IPO firms (at least three years before the IPOs). If there is any mis-valuation, it should be more severe for IPO firms than for industry incumbents. Thus, a risk explanation is more probable.

People could still argue that large IPO events are more likely to happen for industries that have a higher valuation ratio, as suggested by various previous studies such as Pagano et al. (1998), Subrahmanyam and Titman (1999), Lowry (2003), and others. Although the abnormal returns measured here already control for market-to-book ratios, it is possible (though unlikely) that the positive abnormal returns are attributable to investor sentiment and/or growth opportunities that are not captured by market-to-book ratios. However, growth opportunities and/or investor sentiment uncaptured by market-to-book ratios are both industry-wide factors. Neither can reconcile the different return patterns between IPO firms and incumbents. Furthermore, it is unlikely that the average industry can have a persistent improvement in growth opportunities, and thus growth opportunities can hardly explain why the positive alphas of incumbent firms persist for a period of three years. Alternatively, several studies have found that firms are more likely to go public following a period of favorable investor sentiment and eventually earn lower returns as the market cools down (Baker & Wurgler, 2000; Lowry, 2003; Lowry & Schwert, 2002). However, these studies predict that incumbents should exhibit lower returns during the post-issuance period rather than the positive alphas observed in our data.

[23] We skip the first month after the IPO for the IPO portfolio to mitigate the effect of initial price increases after the IPO. For consistency, we also skip the first month after IPO to form the incumbent portfolio.

Table 4. Long-term stock performance

	IPO calendar-time portfolio				*Incumbent calendar-time portfolio*				*IPO incumbent*			
	CAPM	***Fama-French 3***	***Fama-French 4***	***Fama-French 5***	***CAPM***	***Fama-French 3***	***Fama-French 4***	***Fama-French 5***	***CAPM***	***Fama-French 3***	***Fama-French 4***	***Fama-French 5***
alpha	-0.176%	-0.279%	-0.239%	-0.213%	0.880%	0.631%	0.729%	0.531%	-1.076%	-1.053%	-1.137%	-0.093%
	-0.26	-0.81	-0.83	-0.65	3.09	3.21	3.59	2.79	-2.71	-2.69	-2.79	-2.21
Mkt-Rf	1.179	1.193	1.147	1.137	1.256	1.082	1.003	1.001	-0.072	-0.073	-0.093	-0.069
	8.87	11.99	10.39	11.13	23.29	21.56	16.57	14.76	-0.63	-0.79	-0.89	-0.063
SMB		0.671	0.725	0.673		0.832	0.867	0.874		-0.149	-0.171	-0.178
		5.33	6.13	5.79		12.19	12.31	12.11		-1.74	-1.72	-1.76
HML		0.432	0.381	0.371		0.117	0.067	0.059		0.353	0.375	0.305
		3.89	3.61	3.47		0.38	0.98	0.87		3.35	3.47	2.93
UMD			-0.177				-0.165				0.073	
			-2.23				-2.31				0.79	
RMW				-0.124				0.111				0.210
				-1.63				1.71				1.95
CMA				-0.101				0.135				0.198
				-1.31				1.46				1.67
Adj. R^2	0.5998	0.7097	0.7207	0.7358	0.7229	0.8756	0.8911	0.9037	0.0673	0.1267	0.1254	0.1311

Notes: The table documents the monthly returns of industry incumbents within three years after large IPO events in the same industry. The monthly returns are calculated following the calendar-time portfolio method. Mkt-Rf is the market excess return. SMB and HML are size and B/M factor-mimicking portfolio returns. UMD is the momentum factor returns; RMW is the profitability factor and CMA stands for the investment factor. Monthly data of Mkt-Rf, SMB, HML, UMD, RMW, and CMA are available from Ken French's website. T-statistics are adjusted using Newey-West correction for 5-lag of autocorrelations.

4.4. Risk explanation of incumbents' abnormal returns (*H4a* and *H4b*)

A risk explanation would attribute the observed positive alphas of industry incumbents to additional risk uncaptured by included factors (market risk, size, value, and momentum). To examine whether a risk explanation is plausible, we follow the time-series ICAPM method employed by Hou and Robinson (2006). Within the ICAPM framework, risk means loss during bad times (i.e., recessions). Specifically, we examine whether incumbent firms experience losses when the macro economy is in a downturn.

We estimate the following time-series regression of monthly returns of an incumbent portfolio on several macroeconomic variables that are commonly accepted as indicators of business cycles, controlling for existing factors:

$$r_t = \alpha + \sum_{j=1}^{J} \beta_j F_{j,t} + \sum_{k=1}^{K} \gamma_k X_{k,t} + \varepsilon_t \qquad (2)$$

where, dependent variable r_t is the monthly return for incumbent firm portfolio in month *t*; $F_{j,t}$ is the return to the factor-mimicking portfolio of risk factor *j* in month *t*; $X_{k,t}$ is the month *t* value of the macroeconomic variable *k* (*J* is the number of risk factors in total, *K* is the total number of economic variables); and a is the intercept of the above regression.

Macroeconomic variables which are generally acceptable as having predictive power for stock returns are included in the above regression. The monthly inflation rate (*INF*) is calculated using the current consumer price index (CPI) published monthly by the Bureau of Labor Statistics (BLS). Term spread (*Term*) is the difference between the 10-year and 1-year treasury constant maturity rates. Default premium (*DEF*) is the difference between Moody's Baa and Aaa monthly bond yield. These data (including T-bill rate) are obtained from the Federal Reserve Bank of St. Louis through *FRED*. The dividend yield is obtained from Welch and Goyal's (2008) dataset.

Since inflation rate, term spread, default premium, and dividend yield are quite persistent over time, we use the innovation term of these five variables as indicators of business cycles, which is the difference between the current value and lagged value one period before (Chen, Roll, & Ross, 1986). When *ΔINF* is high or *ΔDIV*, *ΔTerm*, and *ΔDEF* are low, the economy is likely in expansion. In contrast, when *ΔINF* is low or *ΔDIV*, *ΔTerm*, and *ΔDEF* are high, the economy is likely to be in recession. We also include monthly returns of SMB, HML, and UMD portfolios (from Ken French's data library) in the regression. Table 5, Panel A reports the estimated results of equation (2) on the returns of incumbent firms before and after large IPO events, respectively. Post refers to the incumbent portfolio returns during the month [+1, +37] subsequent to large IPO events. Prior refers to the returns of the incumbent portfolio during the month [-37, -1] before large IPO events.

Panel A of Table 5 shows that monthly incumbent portfolio returns after IPO events are negatively related to *ΔDEF* and *ΔDIV*. Since *ΔTerm*, *ΔDEF*, and *ΔDIV* tend to increase during the economic recession, this means that incumbent firms on average bear losses during recessions. Loadings on *ΔDEF* and *ΔDIV* are significant, while the estimated coefficient for *ΔTerm* is insignificant. *ΔINF* is significantly positively related to incumbent portfolio returns, implying that incumbent portfolios tend to have higher returns during economic expansion and lower returns when the economy takes a downturn. The estimated coefficient for *ΔT-bill* is positive but insignificant. In general, the results show that incumbent firms tend to have higher returns during good times but perform worse during recession periods. This is consistent with *H4a* and suggests that the abnormal returns observed for incumbents after IPO events are likely to be explained by the additional risk.

Table 5. Time series regression of incumbent return on risk factors and economic variables

Panel A: Time series regression on macroeconomic variables

Post											***Pre***	
Intercept	***Mkt-Rf***	***SMB***	***HML***	***UMD***	***ΔINF***	***ΔTerm***	***ΔDEF***	***ΔDIV***	***ΔT-bill***	***Adj. R^2***	***Coefficient***	***DIFF***
0.0073	1.0013	0.8571	0.0699	-0.1651	1.1792					0.8997	1.005	0.169
3.71	17.1	12.49	1.13	-2.49	2.12						2.31	1.31
0.0071	0.9981	0.8637	0.0571	-0.1701		-0.3347				0.8913	0.938	-1.265
3.47	16.32	12.21	0.89	-2.61		-0.53					2.45	-1.77
0.0073	0.9745	0.8557	0.0431	-0.1667			-3.7123			0.8957	-3.278	-0.556
3.98	17.67	11.79	0.65	-2.47			-3.65				-2.91	-1.85
0.0076	0.9401	0.8543	0.0132	-0.1507				-0.0792		0.8979	-0.025	-0.061
4.21	16.47	11.97	0.21	-2.13				-4.23			-1.19	-2.43
0.0075	0.9832	0.8655	0.0481	-0.1773					1.7214	0.8912	-0.182	1.801
4.01	18.02	12.01	0.79	-2.69					1.54		-0.21	1.71

Panel B: Time series regression on factor-mimicking portfolio returns

Post											***Pre***	
Intercept	***Mkt-Rf***	***SMB***	***HML***	***UMD***	***ΔINF_F***	***ΔTerm_F***	***ΔDEF_F***	***ΔDIV_F***	***ΔT-bill_F***	***Adj. R^2***	***Coefficient***	***DIFF***
0.75%	1.013	0.837	0.119	-0.148	5.044					0.9061	3.057	2.649
4.15	20.47	15.02	2.18	-2.51	3.57						3.11	2.71
0.74%	1.005	0.885	0.055	-0.165		-1.401				0.9023	1.883	-3.267
3.63	18.03	13.02	0.85	-2.47		-0.85					1.54	-1.64
0.54%	0.948	0.821	0.027	-0.157			-9.996			0.8997	-10.855	0.854
2.66	20.11	12.79	0.43	-2.18			-4.27				-5.00	0.26
0.60%	0.877	0.849	-0.048	-0.131				-0.187		0.9089	-0.127	-0.061
2.91	17.98	12.03	-0.74	-1.58				-2.38			-2.47	-0.87
0.59%	0.951	0.867	0.021	-0.169					8.413	0.9087	6.236	2.249
2.97	20.12	14.57	0.32	-2.39					2.69		3.07	0.78

Panel C: Correlations of macroeconomic variables and factor-mimicking portfolio

	ΔINF	***ΔTerm***	***ΔDEF***	***ΔDIV***	***ΔT-bill***	***ΔINF_F***	***ΔTerm_F***	***ΔDEF_F***	***ΔDIV_F***	***ΔT-bill_F***
ΔINF	**1.000**									
ΔTerm	0.118	**1.000**								
ΔDEF	**-0.239**	0.034	**1.000**							
ΔDIV	**-0.176**	-0.051	**0.516**	**1.000**						
ΔT-bill	-0.044	**-0.589**	**-0.242**	**-0.153**	**1.000**					
ΔINF_F	**0.468**	0.086	**-0.136**	-0.121	**0.117**	**1.000**				
ΔTerm_F	0.082	**0.476**	0.003	-0.004	**-0.156**	0.169	**1.000**			
ΔDEF_F	**-0.121**	0.002	**0.541**	**0.424**	**-0.299**	**-0.255**	0.005	**1.000**		
ΔDIV_F	**-0.101**	-0.003	**0.368**	**0.613**	**-0.251**	**-0.198**	-0.005	**0.665**	**1.000**	
ΔT-bill_F	0.143	-0.187	**-0.403**	**-0.387**	**0.403**	**0.296**	-0.396*	**-0.742**	**-0.629**	**1.000**

Panel D: Time series regression on multiple factors

		Intercept	***Mkt-Rf***	***SMB***	***HML***	***UMD***	***ΔINF***	***ΔTerm***	***ΔDEF***	***ΔDIV***	***ΔT-bill***	***Adj. R^2***
Macro-economic variables	post	0.0081	0.9401	0.8491	0.0234	-0.1621	1.0978	0.9001	-4.0191	-0.0574	1.5130	0.9008
		4.73	18.41	12.12	0.44	-2.48	2.86	0.32	-2.61	-2.73	1.31	
	pre	0.0071	0.9752	0.7289	0.2746	-0.2829	0.8510	0.1834	-1.1271	0.0171	0.4657	0.9065
		4.92	26.85	8.86	4.40	-8.26	1.98	2.35	-1.08	0.70	0.49	
	DIFF						0.5973	-0.9302	-1.8467	-0.0683	0.9193	
	t-stat						1.02	-1.27	-1.54	-2.41	0.77	
		Intercept	***Mkt-Rf***	***SMB***	***HML***	***UMD***	***ΔINF_F***	***ΔTerm_F***	***ΔDEF_F***	***ΔDIV_F***	***ΔT-bill_F***	
Factor-mimicking portfolios	post	0.71%	0.983	0.835	0.081	-0.140	4.789	-2.291	-7.383	-0.028	-3.310	0.9185
		3.09	16.18	14.55	1.14	-2.11	2.16	-1.23	-1.75	-0.31	-0.63	
	pre	0.34%	0.960	0.686	0.297	-0.281	2.009	2.197	-1.990	0.050	0.157	0.9139
		1.89	18.52	7.59	3.43	-6.97	1.53	1.77	-3.03	0.78	0.05	
	DIFF						3.635	-4.095	-3.217	-0.079	-3.215	
	t-stat						1.78	-2.001	-1.61	-0.73	-0.44	

Notes: This table presents the results of the times series regression of incumbent firms' monthly returns on various risk factors and economic variables. MktRf is the market excess return. SMB and HML are the returns to size portfolio and value. UMD refers to the momentum factor as in Carhart (1997). Data regarding risk factors come directly from Ken French's website. INF is the monthly inflation rate, which is calculated using the current consumer price index (CPI) published monthly by the Bureau of Labor Statistics (BLS). Term spread (Term) is the difference between the 10-year and 1-year treasury constant maturity rates. Default premium (DEF) is the difference between Moody's Baa and Aaa monthly bond yield. These data, along with the T-bill rate, are obtained directly from the Federal Reserve Bank of St. Louis through FRED. Dividend yields come from Welch and Goyal's (2008) dataset. ΔINF, ΔTerm, ΔDEF, ΔDIV, and ΔT-bill refer to the innovations between the current value and the lagged value one period before for all economic variables. ΔINF_F, ΔTerm_F, ΔDEF_F, ΔDIV_F, and ΔT-bill_F represent the factor-mimicking portfolio, constructed by regressing change in macroeconomic variables on the 25 size and B/M portfolio returns and calculating the fitted value. Post refers to the portfolio returns of incumbent firms during the month [+1, +37] subsequent to large IPO events; prior refers to the portfolio constructed by included returns from industry incumbent firms during the month [-37, -1] before large IPO events. Panel A documents the estimated results using raw numbers; Panel B documents the results using factor-mimicking portfolios. In the second-to-last columns of Panel A and Panel B, we report the estimated coefficients from the same regression but with incumbent firm returns before the IPO as the dependent variable. The last columns of Panel A and Panel B document the differences and t-statistics between the post-issuance loading and pre-issuance loading on each macroeconomic factor and factor-mimicking portfolios. Panel C provides the correlation between the macroeconomic variables employed in this paper and their factor-mimicking portfolios. Bold numbers mean significant correlation at least at the 5% level. Panel D documents the results using several macroeconomic variables and factor-mimicking portfolios all together, and the differences of coefficient loadings before the IPO and after the IPOs. T-statistics are reported.

To investigate in more detail whether it is the IPO events that influence incumbent firms' performance, we compare the loadings of incumbents' returns on these economic factors during the pre-IPO period with those during the post-IPO period. If IPOs can exert competitive pressure on industry incumbents and thus increase their risk, we expect incumbent firms' returns to become more sensitive to economic conditions after large IPO events in the same industry (*H4b*).

We repeat the previous regression of equation (2) using incumbent firm returns before the IPO, that is, from the month [-37, -1] as the dependent variable[24]. In the very last column of Table 5, Panel A, we document the differences and t-statistics between the post-issuance loading and pre-issuance loading on each macroeconomic factor.

The results show that compared with the pre-IPO period, incumbents become more sensitive to *ΔTerm*, *ΔDEF*, *ΔDIV*, and *ΔT-bill*. In particular, the significant change of -0.056 on the estimated coefficients of *ΔDEF* suggests that after large IPO events, incumbent firms have even lower returns during an economic recession. The negative loadings on *ΔDIV* are more than triple (0.025 prior vs. 0.079 post). During the pre-IPO period, an increase in *ΔDIV* by one standard deviation (0.078) is only related to a -0.195% decrease in monthly returns. In comparison, during the post-IPO period, an increase in *ΔDIV* by the same magnitude is associated with a decrease in monthly returns by -0.616%. The difference suggests that during economic downturns, incumbent firms have even lower returns (approximately -0.4%) after IPOs and the magnitude is also economically significant at over -5% annually. The implication of the increased negative loadings on *ΔDEF* and *ΔTerm* is similar. Overall, *H4b* is supported.

Panel B of Table 5 replicates the same regressions as in Panel A but substitutes macroeconomic variables with their traded factor-mimicking portfolio. In brief, all results in Panel A continue to hold. Incumbent portfolio returns are always significantly positively related to *ΔINF* and *ΔT-bill* and negatively significantly related to surprises in *ΔDEF* and *ΔDIV*. Comparing the changes in loadings before and after large IPO events, we can see that the loading on ΔINF increased significantly after large IPO events, suggesting that incumbent firms become more sensitive to economic conditions. While the decrease in the loadings on *ΔTerm* is close to marginally significant, the other changes in loadings are insignificant but with the expected signs. One explanation of the insignificant results may be that there is the only mild correlation between the actual economic variables and returns of the factor-mimicking portfolios. In Table 5, Panel C, we provide the correlations among the macroeconomic variables and their factor-mimicking portfolio returns, the absolute value of which range from 0.002 to 0.742.

The top half of Panel D of Table 5 documents results from regressing the incumbent portfolio returns during both the pre-IPO period and post-IPO period on all macroeconomic variables, while the bottom part reports regression results using factor-mimicking portfolios. It also reports the changes in loading during the post-IPO period versus the pre-IPO period. The results are consistent with the findings in Panels A and B of Table 5. Specifically, the stock performances of incumbents load more negatively on *ΔTerm*, *ΔDEF*, and *ΔDIV* after large IPO events in the industry, consistent with *H4b*. The coefficients for *ΔTerm* and *ΔDEF* are only significant in the factor-mimicking portfolio regression, while those for *ΔDIV* are only significant with macroeconomic variable regressions. The performance also loaded more positively with *ΔINF* using the factor-mimicking portfolio. The changes in loading on *ΔT-bill* are ambiguous.

It is worth noting from the results in Panel B and the bottom part of Panel D of Table 5 that even after controlling for macroeconomic conditions using factor-mimicking portfolio returns, the intercepts reported for post-IPO issuance returns are still significantly positive. For example, in the bottom part of Panel D, the intercept for the post-issuance period is a significant 0.7%. One explanation is that, as Hou and Robinson (2006) suggest, the risk associated with increased competition is not captured by existing factors and economic variables. In contrast, the intercept for the pre-IPO period is much smaller at 0.34%, and only marginally significant. This suggests that risk related to competition becomes much greater during the post-IPO period compared with the pre-IPO period. Hou and Robinson (2006) further suggest that this competition risk is positively related to distress risk and innovation risk. In the following section, we investigate directly how the default probability changes for industry incumbents after large IPO events.

4.5. Changes in default probability of industry incumbents after large IPO events (*H5*)

If industry incumbents' positive returns during the post-issuance period come from enhanced within-industry competition, we should observe a higher default risk for industry incumbents during the post-issuance period (*H5*). Specifically, we use the default probability model developed by Campbell et al. (2008) to estimate a dynamic logistic regression with an IPO indicator to predict the default probability for all incumbent firms over the period between 1995 and 2019. The estimated coefficient on the IPO indicator measures the incremental explanatory power of IPO events in regard to the distress probability of industry incumbents. According to *H5*, we expect the coefficient on the IPO indicator to be positive.

We define failure using CRSP delisting codes following Demers and Joos (2007). Firms with the delisting code for liquidation (400) and involuntary delisting (500, 520, 550, 551, 552, 560, 561, 570, 573, 574, 580, 581, 582, 583, 584, 585) are defined as failure. This method excludes firms that switch exchanges (501) or voluntarily delist (503). We apply the firm failure model of Campbell et al. (2008) and use a dichotomous outcome variable that equals 1 if the firm fails in a particular year as the dependent variable. The model includes the following predictor variables: *NIMTA* is the ratio of net income to the market value of assets and is used to measure profitability; *TLMTA* is the ratio of total liability to the market value of assets; *CASHMTA* is the ratio of a firm's cash and short-term assets to the market value of its assets; *MB* is the firm's market-to-book ratio; *RSIZE* measures the relative size of each firm as the log ratio of its market capitalization to the total market value of the S&P 500 index; *SIGMA* is the annualized

[24] For brevity, we do not document the loadings on SMB, HML, UMD, and Mkt-Rf for returns before IPOs.

standard deviation of daily stock return over the previous three months; *EXRET* is the monthly log excess return on each firm's equity relative to the S&P 500 index.

Table 6 reports the estimated coefficients, odds ratio, and t-statistics from the dynamic logistic regressions. An odds ratio larger than 1 implies a positive relationship between the variable value and probability of default, while an odds ratio smaller than 1 implies a negative relationship between the variable and probability of default. In column 1, we use the predictor variables proposed by Campbell et al. (2008) to estimate the probability of failure for all firms during our sample period. We find that *NIMTA*, *CASHMTA*, *RSIZE*, and *EXRET* are negatively related to a firm's probability of failure, while *TLMTA* and *SIGMA* are positively related to the probability of failure. All coefficients are significant with the expected signs. The model has a pseudo-R^2 of 0.3134. The results are similar to those documented by Campbell et al. (2008). In column 2, we replicate Campbell et al.'s (2008) model for the incumbent firm sample. The results are similar to those documented in column 1 except that the estimated coefficient of *CASHMTA* and *SIGMA* become insignificant, though they still have the expected sign[25].

In column 3, we add into the model an indicator variable, IPO, which equals 1 for a firm-year observation if a large IPO event happened in the same industry as the firm during the past four years, otherwise 0. The estimated coefficient of the IPO indicator is a significantly positive 1.21, suggesting that the IPO indicator contains failure-related information that is not captured in the existing predictor variables. Specifically, it indicates that the default probability for industry incumbents increases after large IPO events, consistent with *H5*. The odds ratio of 3.36 implies that the probability of default during the post-IPO period is more than doubled compared with the pre-IPO period. Using the actual default probability in the incumbent sample, which is 1% (= 535/52,786), this means that the default probability increases by 2.36% after large IPO events[26]. In the untabulated result, we estimate the model using the IPO indicator alone, that is, without other predictor variables, to investigate whether the correlation between the predictor variables and the IPO indicator drives the results in column 3. The estimated coefficient of the IPO indicator (1.27) continues to be positive and significant, with an odds ratio of 3.55, confirming the earlier result. In sum, the results in Table 6 suggest that industry incumbents have a higher default probability after large IPO events in their industry, consistent with *H5*.

One may argue that the results in previous sections are driven by the correlation between IPO and some other omitted variables that increase firms' default probability. For example, it is likely that the IPO indicator simply captures the mean reversion of industry growth. To address this concern, we conduct cross-sectional tests based on the characteristics of industry incumbents. If incumbents that are expected to be affected more by IPO firms are also more likely to have increased default probability, the endogeneity concern due to omitted variables could be mitigated.

Intuitively, the investment flexibility, growth opportunities, and profitability of incumbent firms can help mitigate the enhanced competition imposed by newly-listed firms. We use Tobin's Q to capture a firm's growth opportunity and leverage and Altman Z-score to capture its investment flexibility (higher-leverage and more constrained firms have less investment flexibility). If the increase in default probability comes from the competitive effects imposed by large IPOs, incumbent firms with more financial flexibility, growth opportunity, and better performance should be more resilient and thus exhibit less increase in their default probability after large IPO events. Alternatively, if mean reversing is behind all previously observed phenomena, there should either be no cross-sectional differences in the increases of incumbents' default probability, or larger firms with better performance should exhibit a bigger increase in their default probability (as they are further away from the mean).

In Table 6, Panel B, we estimated the same default probability prediction model with IPO indicators for different subsamples of industry incumbents. Specifically, industry incumbents are sorted according to their most recent pre-IPO profitability, Tobin's Q, leverage, and Altman Z-score. Firms in the bottom 30% of each measure are assigned to the low portfolio, while firms in the top 30% are assigned to the high portfolio. We expect that industry incumbents with higher profitability, Tobin's Q, and Altman Z-score but lower leverage will have less increase in their default probability after large IPO events (smaller loading on the IPO indicator).

The results documented in Table 6 Panel B are consistent with our prediction. For example, industry incumbents with the lowest Altman Z-score (the least financial flexibility) will have more than tripled default probability after large IPO events (odds ratio = 4.3), while firms with the highest Altman Z-score (the most investment flexibility) will only exhibit 1.8 times increase in their default probability (odds ratio = 2.84). Similarly, firms with higher profitability and more growth opportunities but lower leverage also experience less increase in their default probability. In sum, the above results from cross-sectional tests alleviate the endogeneity concern that our results are driven by omitted variables that could capture the mean reversion of industry growth.

[25] One reason might be that the incumbent firms included in our sample are established firms that have relatively stable cash holdings and less volatility (by our sample filtering criteria, incumbent firms have stayed public for at least four years), and thus *CASHMTA* and *SIGMA* exhibit little predictive power for default probability.

[26] The absolute magnitude of default probability is small since the incumbent firm sample includes large and established firms.

Table 6. Dynamic logistic regression of default probability with IPO indicator

Panel A: Dynamic logistic regression of default probability			
	All	***Incumbents***	
	1	***2***	***3***
Intercept	-10.597	-11.479	-11.375
IPO			1.21
			3.356
			(11.47)
NIMTA	-3.479	-4.227	-3.806
	0.031	0.015	0.022
	(-16.59)	(-8.47)	(-7.75)
TLMTA	1.213	2.279	2.134
	3.364	9.767	8.449
	(14.37)	(10.41)	(9.65)
MB	0.198	0.207	0.215
	1.219	1.230	1.240
	(15.65)	(7.47)	(7.45)
RSIZE	-0.427	-0.463	-0.457
	0.652	0.629	0.633
	(-26.76)	(-12.83)	(-12.51)
CASHMTA	-1.715	-0.025	-0.263
	0.180	0.975	0.768
	(-7.81)	(-0.03)	(-0.45)
SIGMA	1.019	0.020	1.397
	2.770	1.020	4.043
	(12.85)	(0.08)	(0.47)
EXRET	-7.045	-4.903	-5.445
	0.001	0.007	0.004
	(-23.07)	(-6.33)	(-6.85)
No. of failure	3267	535	
N	128,432	52,786	
Pseudo R^2	0.3134	0.2467	0.2972

Panel B: Dynamic logistic regressions for subsamples								
	Profitability		***Leverage***		***Tobin's Q***		***Altman Z-score***	
	Low	***High***	***Low***	***High***	***Low***	***High***	***Low***	***High***
	1	***2***	***5***	***6***	***3***	***4***	***5***	***6***
IPO	1.434	1.118	1.088	1.271	1.362	1.176	1.460	1.044
	4.195	3.058	2.970	3.563	3.903	3.242	4.306	2.841
	(10.70)	(4.54)	(4.94)	(8.51)	(8.94)	(5.60)	(10.26)	(4.26)
NIMTA	-3.691	-5.067	-5.769	-3.779	-3.690	-4.678	-3.522	-6.134
	0.025	0.006	0.003	0.023	0.025	0.009	0.030	0.002
	(-5.65)	(-4.15)	(-5.30)	(-5.30)	(-5.32)	(-4.37)	(-5.21)	(-5.03)
TLMTA	2.087	3.145	2.627	1.983	1.652	2.169	1.827	1.743
	8.059	23.220	13.831	7.263	5.217	8.749	6.213	5.716
	(7.63)	(5.36)	(5.58)	(5.40)	(4.78)	(5.32)	(6.06)	(3.22)
MB	0.242	0.135	0.266	0.197	0.091	0.268	0.166	0.228
	1.273	1.145	1.305	1.218	1.095	1.308	1.180	1.256
	(6.73)	(1.80)	(4.20)	(5.14)	(1.65)	(4.96)	(4.54)	(2.88)
RSIZE	-0.485	-0.299	-0.415	-0.433	-0.404	-0.454	-0.448	-0.367
	0.616	0.742	0.660	0.648	0.668	0.635	0.639	0.693
	(-9.79)	(-4.00)	(-5.15)	(-8.77)	(-7.89)	(-6.15)	(-9.17)	(-4.47)
CASHMTA	-0.442	2.418	0.535	-0.750	-1.134	0.756	-0.528	0.342
	0.643	11.227	1.708	0.472	0.322	2.130	0.590	1.407
	(-0.69)	(1.14)	(0.56)	(-0.96)	(-1.61)	(0.76)	(-0.78)	(0.31)
SIGMA	2.472	-2.114	-0.055	0.396	1.721	2.245	0.164	-0.370
	17.570	0.121	0.947	1.486	5.590	9.443	1.179	0.691
	(0.64)	(-0.25)	(-0.13)	(1.47)	(0.39)	(0.36)	(0.63)	(-0.79)
EXRET	-4.877	-6.728	-4.703	-3.946	-6.063	-6.235	-5.080	-6.950
	0.008	0.001	0.009	0.019	0.002	0.002	0.006	0.001
	(-4.94)	(-3.30)	(-2.94)	(-3.58)	(-4.99)	(-4.27)	(-4.91)	(-3.90)
No. of failure	340	103	123	273	271	135	301	98
N	20896	23109	21886	20357	21691	18974	20803	19871
Pseudo R^2	0.3068	0.2135	0.2677	0.2809	0.2517	0.3196	0.2913	0.2230

*Notes: Panel A documents the estimated results from the dynamic logistic regression of the default probability model with the IPO indicator. The model is estimated with the predictor variables for all industry incumbent firms between 1995 and 2018. The dependent variable is a dummy variable that equals 1 if the firm is delisted in a given year. All independent variables are measured the year before the failure event. NIMTA is the ratio of net income to the market value of assets and is used to measure profitability. TLMTA is the ratio of total liability to the market value of assets. SIGMA is the annualized standard deviation of daily stock return over the previous three months. MB is the firm's market-to-book ratio. RSIZE measures the relative size of each firm as the log ratio of its market capitalization to the total market value of the S&P 500 index. CASHMTA is the ratio of a firm's cash and short-term assets to the market value of its assets. EXRET is the monthly log excess return on each firm's equity relative to the S&P 500 index. Panel B reports the different estimated results from the dynamic default probability model for different portfolios of incumbent firms. We sort industry incumbent firms first according to their most recent profitability, leverage, Tobin's Q, and Altman Z-score. Profitability is defined as net income scaled by total assets. Leverage is defined as long-term debt scaled by the market value of assets. Tobin's Q is the ratio of the market value of assets to the book value of assets. Altman Z-score is defined following the coefficients in Altman (1968) as 3.3 * earnings before interest and taxes/total assets + 0.99 * sales/total assets + 1.4 retained earnings/total assets + 0.6 * market capitalization/long-term debt + 1.2 * working capital/total assets. For each IPO event, incumbent firms in the top 30% are included in the high ratio sample, while firms in the bottom 30% are included in the low ratio sample. Numbers on top are the estimated coefficients, numbers in the middle are the corresponding odds ratio, and t-statistics are reported at the bottom.*

4.6. Cross-sectional analysis of incumbent firms' positive abnormal return (*H6a, H6b, H6c, H6d, H6e*)

The evidence documented above is consistent with the explanation that large IPO events enhance competition, exert more competitive pressure on incumbents, and increase their default risk. Furthermore, if greater competition contributes to the risk and positive abnormal returns of industry incumbents observed in the data, we expect industry competition to be related to incumbent firms' expected stock returns. In this section, we try to shed more light on how differences across industries affect IPO-related competitive effects by examining how various aspects of competition relating to the stock returns of incumbents (*H6a*, *H6b*, *H6c*, and *H6d*).

4.6.1. Industry concentration/competitiveness (H6a)

Hou and Robinson (2006) show that firms in concentrated industries with higher Herfindahl index (less competitive) earn on average lower returns than firms operating in competitive industries with lower Herfindahl index (more competitive). The differences in returns cannot be explained by existing factors such as size (*SMB*), book-to-market (*HML*), and momentum (*UMD*). This supports our story of increased competition risk for industry incumbents. However, people might argue that our previous results overlap with Hou and Robinson's (2006) and are not associated with IPO-related advantages. Specifically, people could argue that after large IPO events, the entire industry becomes more competitive and thus, incumbents have higher returns. However, if this is the case, IPO firms should also have higher returns, rather than the lower returns observed in numerous previous studies (i.e., the IPO underperformance puzzle).

To further rule out this possibility, we estimate the effect of IPO events on incumbent firms' cost of equity using an IPO indicator and controlling for industry concentration (measured with the Herfindahl index) and existing factors that affect firm returns. We estimate the following regression:

$$R_{i,t} = \alpha + \beta_0 * IPO_{i,t} + \beta_1 * HHI_{i,t-1} + \beta_2 * IPO_{i,t} * HHI_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,t-1} + \varepsilon_{i,t} \quad (3)$$

where, $R_{i,t}$ is a monthly return for incumbent firm i in calendar month t. IPO is a dummy variable that equals 1 if month t is within the 36 months post large IPO events in incumbent firm i's industry, and 0 otherwise. $HHI_{i,t}$ denotes the Herfindahl index for firm i's industry at month t, which is calculated as the sum of squared market share for all firms in that industry. The lower the value of the Herfindahl index, the more competitive the industry[27]. $X_{k,t}$ is the value in month t for the control variable X known to be related to stock returns, including beta, size, market-to-book ratios, and past six-month returns. Since the probability of a firm going public is related to market liquidity, we control for stock liquidity with Roll's (1984) measure. α is the intercept of the above regression. Firms' market beta is estimated as in a Fama-Macbeth regression[28]. We also include the interaction term of the IPO dummy and industry concentration in our regression in order to examine the effect of IPOs on incumbents for different industries. To rule out unobservable industry heterogeneity and to control for serial correlation, we estimate the above model using Fama-Macbeth regression with industry dummies. Note that the explanatory variables are all lagged by one period so that the estimated results can be explained as the effects of IPOs on incumbent firms' expected returns.

Table 7, Panel A documents the summary statistics of all the competition measures used in this section, and Panel B documents the Pearson correlation among all competition measures. The distribution of our calculated measures and correlations among them are similar to those reported by Karuma (2007). Table 8 reports the estimated results of equation (3). Column 1 shows that industry incumbents in concentrated industries on average earn lower returns than those in less concentrated industries, as suggested by the significantly negative loading on the Herfindahl index of -0.0243. This is consistent with the findings of Hou and Robinson (2006). In column 3, we add the IPO indicator, and the result shows that incumbent firms experience a significant increase of 5.4% in their stock returns after large IPO events. The estimated coefficient for the interaction term of IPO indicator and industry Herfindahl index is negative, implying that the associated increase in returns is less for concentrated industries but larger for more competitive industries. However, the difference is insignificant, inconsistent with *H6a*. One plausible explanation for the insignificance is that industry concentration is a noise measure of product market competition (Karuma, 2007), which implies either strong competition or less competition[29]. Karuma (2007) further shows that conditional on industry concentration, market size, entry cost, and product differentiability are also related to competition. To explore the relationship between competition and incumbent firms' expected return in more detail; we use other measures as in Karuma (2007) in the next session.

[27] We acknowledge that data availability constrains the calculation of the Herfindahl index, but this is the most commonly used index to measure industry competition. We also use the four-firm concentration ratio as an alternative, and the results are quite similar with those estimated with the Herfindahl index.

[28] Market beta is estimated as the sum of the coefficients of regressions of individual firms' monthly stock returns on contemporaneous and lagged market returns over the past three years.

[29] Firms in concentrated industries usually face weak competition and thus are less experienced in dealing with competitors. However, they have more market power and are relatively immune to small listing firms. This situation generates the overall insignificant differences between concentrated industries and competitive industries.

Table 7. Descriptive statistics for industry concentration and competition

Panel A: Summary statistics of various competition measures				
	Mean	***Median***	***Q1***	***Q3***
HHI	0.54	0.56	0.42	0.67
DIFF	1.39	1.12	1.09	1.19
MktSize ($M)	286269.79	129920.00	54346.29	371075.44
log (MktSize)	11.82	11.77	10.90	12.82
EntCost ($M)	9948.46	4792.56	2383.36	9438.72
log (EntCost)	8.50	8.47	7.78	9.15
Fnum	209.70	138.00	60.00	291.00
log (Fnum)	4.85	4.92	4.09	5.67
Panel B: Pearson correlation				
	HHI	***DIFF***	***MktSize ($M)***	***EntCost ($M)***
HHI	1.000			
DIFF	**-0.084**	1.000		
MktSize ($M)	**-0.339**	**0.119**	1.000	
EntCost ($M)	**-0.193**	0.020	**0.666**	1.000
Fnum	**-0.514**	**0.158**	**0.472**	**0.087**

Notes: The table provides descriptive statistics for the industry concentration and competition measures used in the analyses. HHI represents the Herfindahl index, calculated as the sum of squared market shares for all firms in each industry. DIFF represents product differentiability, which is calculated as industry sales scaled by operating cost (defined as the sum of cost of goods sold (COGS), selling, general, administrative expenses (SG&A), depreciation, and amortization). Market size (MktSize) is calculated as the sum of firm sales in each industry. Entry cost (EntCost) is calculated as the weighted average of firms' PP&E for each industry (weight is individual firm's market share). Fnum denotes the number of public firms. All data come from Compustat Segment files. Panel A documents the distribution of various measures, while Panel B reports their Pearson correlation coefficients. Bold numbers mean significance at 5% level.

Table 8. Effect of IPOs on incumbents' returns, cross-sectional regression on Herfindahl index

	(1)	*(2)*	*(3)*
IPO			0.054
			1.72
HHI	-0.0243	-0.8263	-1.894
	-2.38	-0.84	-1.11
*IPO*HHI*			-0.0214
			-0.96
Beta	0.0035	0.0043	0.0044
	0.7	0.86	0.87
ln(size)	-0.0003	-0.0001	-0.0001
	-0.44	-0.15	-0.12
ln(M/B)	-0.0123	-0.0128	-0.0128
	-7.18	-8.13	-8.19
Past returns	-0.0003	-0.0004	-0.0004
	-1.7	-2.06	-2.03
Liquidity	0.0017	0.0017	0.0017
	4.27	3.99	4.03
Industry dummy	No	Yes	Yes

Notes: This table examines the effect of IPOs on incumbent firms' returns cross-sectionally. It reports estimated results from a panel regression of incumbent firm returns on the Herfindahl Index, an IPO dummy variable, and several known existing risk factors that affect firm returns. Specifically, we estimate the regression as follows:

$$R_{i,t} = \alpha + \beta_0 * IPO_{i,t} + \beta_1 * HHI_{i,t-1} + \beta_2 * IPO_{i,t} * HHI_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,t-1} + \varepsilon_{i,t}$$

where, IPO dummy variable equals 1 if month t is within the 36 months of a large IPO event in firm i's industry, and 0 otherwise. The Herfindahl index is employed to measure industry competition and is calculated as the sum of squared market share for all the firms in each industry.

4.6.2. Other competition measures (H6b, H6c, H6d, H6e)

Product substitutability refers to the likelihood of one product being substituted for another product that is similar and close. A higher level of product substitutability implies that products are hardly differentiable from one another, and thus means a higher level of price competition. We expect that the expected returns of incumbents in industries with higher levels of product substitutability increase more (*H6b*).

Following studies in industrial organization, we use price-cost margin to measure product substitutability in an industry, which is exactly the negative reciprocal of price elasticity of demands (Nevo, 2001). Intuitively, a lower price-cost margin (closer to 1) implies that in such industries, demand is more sensitive to the price change (high price elasticity), and thus the price approaches the true production cost and the industry is closer to perfect competition. Therefore, a lower price cost margin reflects a higher level of product substitutability. We calculate the price-cost margin for each 4-digit SIC code[30], and then average them across each Fama-French 49 industry[31]. We add into the previous regression the measure of product substitutability (DIFF) and an interaction term between IPO and DIFF. We expect the interaction term to be negative (*H6b*).

[30] As of June 1, 1998, IAS 14 Segment Reporting requires reporting of financial information by business or geographical area. While data of segment sales before 1998 are generally available from the Compustat Segment File, data related to operating costs (i.e., segment COGS, segment SGA, and segment depreciation and amortization) are usually missing. To minimize the problem caused by missing data, our analysis starts from year 1998.

[31] The reason for doing this two-stage average instead of averaging over the whole industry directly is to mitigate the effect of extreme value. Price-cost margin might differ within a "wider" industry, where price-cost margins of sub-industries differ greatly. For example, taken from Nevo (2001), the profit margin of the ready-to-eat cereal industry (with SIC code 2043) is 64.4%, while the whole food industry with two digit SIC code 20 is only a little bit over 26.5%.

Other variables associated with product market competition include market size (*MktSize*), number of public firms (*Fnum*), and entry cost (*EntCost*). Large market size is usually associated with high profitability and growth potential, which attracts firms entering the industry. Since industries with large market size are usually in the growth stage and have a higher profit margin, competitive pressure from IPO firms to incumbents is likely being mitigated by the big growth potential. This suggests that IPO-related competitive effects should be negatively related to market size (i.e., the estimated coefficient for the interaction between IPO and market size is expected to be negative; *H6c*).

Entry cost measures the start-up cost for entering the industry. Higher entry cost serves as a barrier to potential competitors, implying that incumbent firms operating in high entry cost industries are likely to lack experience in competing because there are very few potential entrants. Therefore, IPO events are more likely to generate significant negative impacts in industries with higher entry costs (*H6d*).

To explore how IPO-related competitive impacts vary across different industries, we apply the same approach as before but include alternative measures of competition and their interaction with the IPO indicator into the regression. Since these competition measures are skewed, we use the log transformation of these competition measures in the regressions. As shown in Table 7, Panel B, these competition measures are correlated with each other, so we start by estimating the above regression for each competition measure respectively. Table 6, Panel A reports the estimated results.

Column 1 documents the regression results with product differentiability. The significantly negative loading on the interaction term between IPO indicator and DIFF suggests that IPO events in highly differentiable industries have smaller competitive impacts, consistent with *H6b*. All else being equal, firms in industries that have lower differentiability (DIFF_Q1 = 1.09) will experience 0.11% more increase in their monthly returns after large listing events. In contrast, firms in industries with higher differentiability (DIFF_Q3 = 1.19) will experience 0.08% less increase in their monthly stock returns after large listing events.

Similarly, Column 2 shows that incumbent firms' returns increase marginally significantly after large listing events. The estimated coefficient on the interaction between IPO and *MktSize* is negative at -0.0041, but insignificant. The lack of evidence regarding how market size affects IPO-related competitive advantage might be because the inherent growth potential of a bigger market offsets the competitive threat from new entrants.

Column 3 offers some evidence that IPO increases incumbent firms' returns, but no evidence regarding how entry cost affects IPO-related competitive advantages This might be because the measure of entry cost calculated using PP&E is not a good measure of competition. It might have been a good proxy a decade ago, but current technology cost also accounts for an important part of entry cost, especially in some high-tech industries.

Chemmanur et al. (2010) show that the number of public firms (*Fnum*) is associated with industry competition. Industries with a higher number of public firms are more competitive. If this is the case, we expect incumbent firms in industries with a higher number of public firms to experience a bigger increase in their abnormal returns (*H6e*). In column 4, we can see that none of the variables of interest is significant, although all the signs are consistent with our expectations One plausible reason is that the concentration measure (*HHI*) is highly correlated with the *Fnum* (-0.514), which might attenuate the explanatory power.

In Table 9, Panel B, we regress incumbent firms' monthly returns on multiple competition measures at the same time. The sign of the estimated coefficients for each interaction between competition and IPO indicator is the same as in Panel A (except for *EntCost*). The last column includes the estimated results from a kitchen-sink regression. Column 5 shows that after large IPO events, incumbent firms generally experience an increase in their expected stock returns, as indicated by the significantly positive coefficient of 0.1748 for the IPO indicator. Moreover, such increases in incumbent firms' stock returns are larger for industries with a larger number of firms (significant IPO * *Fnum* = 0.04), for industries with smaller growth opportunities (marginally significant IPO * *MktSize* = -0.0112) and for industries with lower differentiability (close to marginally significant IPO * DIFF = -0.0829). In other words, consistent with our hypotheses *H6b*, *H6c*, and *H6e*, the increase in abnormal returns is higher for industries with greater existing competition. Overall, the results suggest that IPOs can enhance product market competition, which consequently increases the expected returns of existing incumbents.

Table 9. Cross-sectional Fama-Macbeth regression on product market competition (Part 1)

Panel A: Regression on each competition measure				
	(1)	*(2)*	*(3)*	*(4)*
IPO	0.102	0.0188	0.0214	0.0427
	2.57	1.52	1.97	0.88
*IPO*DIFF*	-0.0926			
	-2.77			
*IPO*MktSize*		-0.0041		
		-1.07		
*IPO*EntCost*			-0.0017	
			-0.88	
*IPO*Fnum*				0.0073
				0.98
DIFF	0.044			
	0.45			
MktSize		0.0034		
		1.16		
EntCost			0.0922	
			0.94	

Panel B: Regression on multiple competition measures					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
IPO	-0.0187	0.06216	-0.0131	0.0314	0.1748
	-0.32	0.22	-0.31	1.21	1.79
*IPO*DIFF*	-0.0379	-0.1334	-0.0883	-0.0657	-0.0829
	-0.92	-1.83	-1.52	-0.89	-1.59
*IPO*MktSize*	-0.0067	-0.0286	-0.0047	-0.0027	-0.0112
	-1.79	-2.29	-0.99	-0.46	-1.63
*IPO*EntCost*			0.0052	0.004	0.0005
			1.41	1.29	0.14
*IPO*Fnum*		0.1437		0.0201	0.04
		0.88		0.55	1.85
DIFF	0.0976	0.0926	-0.046		0.0917
	1.36	1.46	-0.51		1.68
MktSize	-0.0025	0.0027	0.0032	-0.105	0.0286
	-0.43	0.54	0.77	-0.92	0.43
EntCost			0.0092	0.0108	0.0519
			1.81	1.09	1.52

Table 9. Cross-sectional Fama-Macbeth regression on product market competition (Part 2)

Panel A: Regression on each competition measure

	(1)	(2)	(3)	(4)
Fnum				-0.0039
				-0.47
beta	0.0044	0.0044	0.0044	0.0044
	0.87	0.87	0.87	0.86
ln(size)	-0.0001	-0.0001	-0.0001	-0.0001
	-0.12	-0.13	-0.12	-0.13
ln(M/B)	-0.0128	-0.00128	-0.0128	-0.0128
	-8.18	-8.19	-8.17	-8.18
Past returns	-0.0004	-0.0004	-0.0004	-0.0004
	-2.04	-2.03	-2.03	-2.04
Liquidity	0.0017	0.0017	0.0017	0.0017
	4.08	4.07	4.06	4.06
HHI	-0.192	-0.0839	0.9412	0.1659
	-0.56	-0.38	1.9	0.8
*IPO*HHI*	-0.0128	-0.0085	-0.0235	-0.0137
	-0.61	-0.31	-1.01	-0.63
Industry dummy	yes	yes	yes	yes

Panel B: Regression on multiple competition measures

	(1)	(2)	(3)	(4)	(5)
Fnum		-0.1241		-0.0387	-0.0599
		-0.77		-1.2	-1.06
beta	0.0044	0.0044	0.0044	0.0044	0.0044
	0.86	0.86	0.86	0.86	0.86
ln(size)	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	-0.13	-0.12	-0.12	-0.12	-0.12
ln(M/B)	-0.0128	-0.0128	-0.0128	-0.0128	-0.0128
	-8.18	-8.17	-8.18	-8.18	-8.18
Past returns	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005
	-2.04	-2.04	-2.04	-2.04	-2.04
Liquidity	0.0017	0.0017	0.0017	0.0017	0.0017
	4.07	4.06	4.08	4.07	4.08
HHI	-0.1176		0.073		-0.2876
	-1.13		0.91		-1.22
*IPO*HHI*	0.0062		0.0132		0.0453
	0.26		0.51		0.76
Industry dummy	yes	yes	yes	yes	yes

Notes: This table reports Fama-Macbeth estimates for the equation in the following form:

$$R_{i,t} = \alpha + \beta_0 * IPO_{i,t} + \beta_1 * competition_{i,t-1} + \beta_2 * IPO_{i,t} * competition_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,t-1} + \varepsilon_{i,t}$$

where, IPO dummy variable equals 1 if month t is within 36 months of large IPO events in firm i's industry, and 0 otherwise. Competition measures include product differentiability (DIFF), which is calculated as industry sales scaled by operating cost (defined as the sum of cost of goods sold (COGS), selling, general, administrative expenses (SG&A), depreciation and amortization); market size (MktSize), which is calculated as the sum of firm sales in each industry; entry cost (EntCost), which is calculated as the weighted average of firms PP&E for each industry (weight is individual firm's market share); and a number of public firms. The Herfindahl index is calculated as the sum of squared market share for each industry. Market capitalization and market-to-book ratio are calculated at the end of the previous month. Liquidity is measured using Roll's (1984) liquidity measure. Panel A documents the estimated results of expected return on each competition measure respectively, while Panel B documents the regression results on multiple competition measures. T-statistics adjusted for autocorrelation and heteroskedasticity are reported below each coefficient.

5. ROBUSTNESS TEST

It might be that the previously documented results are specific to our selected samples. To provide robustness tests, we re-do all the tests for different IPO and industry incumbent samples. Specifically, we change the industry identification from Fama-French 49 industry to 3- and 2-digit SIC code, respectively, for IPO firms whose proceeds are in the top 10% during the sample period, and for IPO firms that have the top 30% sales. Results are available upon request. Briefly speaking, the results for the alternative samples are statistically and qualitatively similar.

5.1. Long-term stock return

It is quite an arguable problem how to measure long-term expected returns, but recently much progress has been made to determine which measure is better. In previous sections, we use the calendar-time portfolio method recommended by Fama (1998) and Mitchell and Stafford (2000), but as Mitchell and Stafford (2000) point out, this method also has a weakness as it requires constant loadings on the SMB, HML, and UMD factors. They suggested a method called calendar-time abnormal return-CTAR (first used in Jeffe, 1974) as a robustness test. We replicate this method and get similar significantly positive abnormal returns for our incumbent firms. The results are briefly listed below (Table A.1, Appendix). They show that incumbent firms have positive abnormal returns within three years after large IPO events in the same industry. The magnitude of these abnormal returns is quite similar to those documented in Table 4 for each specific model, confirming that the positive abnormal returns observed for industry incumbents are not an artifact.

5.2. Cash flow shocks

According to Campbell and Shiller's (1988) decomposition, the returns are determined by cash flow shocks and shocks to discount rates. This means that cash flow shocks could be responsible for our previous findings. However, it is unlikely this is the case. First, while positive cash flow shocks could be related to positive excess returns, they rarely persist for three years subsequent to IPO events. Moreover, the results in Table 3 show that the operating performance and profitability of incumbents decline subsequent to listing events in the same industry. Thus, expected post-issuance cash flows for industry incumbents are more likely to fall than to increase. To rule out the possibility, we examine incumbents' earnings/profitability shocks after IPO events.

We measure unexpected profitability for all incumbent firms as the residual from the following earning forecast models, which is similar to the method in Fama and French (2000), Vuolteenaho (2002), and Hou and Robinson (2006):

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_{t-1}}{A_{t-1}} + \alpha_2 DD + \alpha_3 \frac{D_{t-1}}{B_{t-1}} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \epsilon_t \quad (4)$$

where, *E/A* measures firm profitability, calculated as earnings scaled by the book value of total assets; *V/A* is the ratio of the market value of assets to book value of assets; *DD* is a dummy variable for non-dividend-paying firms, and *D/B* is the ratio of dividend payments to book equity. We also add the lagged profitability measure $\left(\frac{E_{t-1}}{A_{t-1}}\right)$ as suggested by Vuolteenaho (2002). The residual from equation (4) captures unexpected profitability.

Table 10, Panel A reports the average estimated results from Fama-Macbeth regressions of the above equation, which are similar to those reported in Hou and Robinson (2006) and Fama and French (2000). Loadings on *D/B* and *DD* are statistically significant with the expected sign. Lagged profitability is highly significant and positively related to current profitability. The inclusion of lagged profitability helps improve the regression R^2 to 48.6% as suggested by Vuolteenaho (2002). The only difference from previous results is that the estimated coefficient on *V/A* reverses its sign. This might be attributable to the fact that our sample period has more weight around the dot com bubble period.

Panel B of Table 10 presents the average (and median) unexpected profitability for industry incumbents for a three-year period before and after IPO events. For incumbent firms, the average unexpected profitability before the IPO events is 1.68% annually. Unexpected profitability declines to 1.16% subsequent to large IPO events, which is around a 30% decrease. The difference in unexpected profitability before and after IPOs is significant, with a t-statistic of 2.61. To address the concern that this result might be driven by outliers, we winsorize unexpected profitability for all observations at the 1% and 5% levels, respectively. The untabulated results are qualitatively the same. The results in Panel B also indicate that the median unexpected profitability decreases from 2.54% before to 2.19% after large IPO events, which is statistically significant with the Wilcoxon rank test.

Table 10, Panel C directly examines the relationship between unexpected profitability of incumbents and IPO by estimating a regression of unexpected profitability on the IPO indicator. The loading on the IPO indicator in column 1 is significantly negative, indicating that unexpected profitability decreases on average by 0.53% after large IPO events for industry incumbents. We include year fixed effect in column 2 estimation to control for time-related factors. The estimated coefficient of the IPO indicator continues to be significantly negative, suggesting that the decline in unexpected profitability is not driven by an unobserved time effect. We include both industry and year fixed effects in column 3 to control for industry heterogeneity. The estimated coefficients of the IPO indicator remain significantly negative.

These results suggest that the unexpected profitability of industry incumbents actually decreases instead of increases after large IPO events. This contradicts the speculation that persistent positive cash flow shocks contribute to the positive alphas of incumbents and confirms that the positive returns observed for industry incumbents after large IPO events are not driven by persistent shocks in cash flow, but rather are attributable to shocks to the discount rate.

It is arguable that the results in Table 10 are based on the assumption that the profitability prediction model is correct. To address this concern, we use alternative measures that do not depend on specific profitability models: earnings surprises. In particular, we compute earnings surprises using both analyst earnings forecasts and historical earnings as proxies for market expectation.

Following Livnat and Mendenhall (2006), the first alternative measure of unexpected earnings is calculated as the difference between actual and expected earnings scaled by price: $SUE1_{i,t} = \frac{(E_{i,t} - E_{i,t-4})}{P_{i,t}}$, where $E_{i,t}$ represents EPS before extraordinary items for firm i in quarter t, $E_{i,t-4}$ represents EPS before extraordinary items for the same quarter in the previous year, and $P_{i,t}$ is the stock price of firm i at the end of quarter t. Although the benchmark for this measure is set to be historical EPS with no adjustment, the advantage of this measure is that it covers most of the Compustat firms. To address the influence of special items, we follow the method used in Bradshaw and Sloan (2002) and Livnat and Mendenhall (2006) and compute our second earnings surprise measures. Specifically, we subtract from the EPS the amount of special items times 65% divided by the number of shares used to calculate earnings per share. Thus, the estimated measure is after the exclusion of special items and is denoted as *SUE2*. Last, we estimate the third earnings surprise measure with analyst forecasts by substituting $E_{i,t-4}$ from the above equation with analysts' expectations and denote it as *SUE3*. This measure incorporates more judgment from sophisticated investors and captures market surprises better. However, the requirement for available analyst earnings forecasts makes it less inclusive.

Table 10. Unexpected profitability and IPO

Panel A: Expected profitability regressions						
	α_0	$(V/A)_{t-1}$	*DD*	$(DB)_{t-1}$	$(E/A)_{t-1}$	*Adj* R^2
E/A	0.012	-0.004	-0.035	0.118	0.719	0.4863
	(2.10)	(-2.35)	(-5.42)	(1.87)	(62.24)	
Panel B: Average unexpected profitability before and after IPO events						
before	mean	1.680%	median	2.536%	t-stat	Wilcoxon
after	mean	1.160%	median	2.187%	2.61	0.0002
Panel C: Regression of unexpected profitability on IPO						
IPO	-0.0053		-0.0056		-0.0023	
t-stat	-2.69		-2.87		-1.51	
R^2	0.0003		0.0072		0.0375	
Industry fixed effect	no		no		yes	
Year fixed effect	no		yes		yes	

Notes: The table examines the relationship between the unexpected profitability of industry incumbents and IPO events. Panel A represents the average estimated coefficients and R^2 of the Fama-Macbeth regression of profitability on firm characteristics in the following form:

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_{t-1}}{A_{t-1}} + \alpha_2 DD + \alpha_3 \frac{D_{t-1}}{B_{t-1}} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \epsilon_t$$

where, E/A is earnings scaled by the book value of total assets, which measures firm profitability; V/A is the ratio of the market value of assets to book value of assets; DD is a dummy variable for non-dividend-paying firms; D/B is the ratio of dividend payments to book equity. R^2 is calculated as the average of all cross-sectional R^2. T-statistics are included in parentheses. Panel B documents the mean and median unexpected profitability for industry incumbents within three years before and after IPO events, where unexpected profitability is the regression residual. Panel C documents the results for cross-sectional regressions of unexpected profitability on IPO indicators. IPO variable is defined as 1 for a firm-year observation if a large IPO event happened in the same industry as the specified firm within a three-year period before that particular year; otherwise, IPO is equal to zero. T-statistics for all coefficients are reported below.

We replicate the previous tests in Table 10 using our measures of earnings surprises: *SUE1*, *SUE2*, and *SUE3*. Table 11, Panel A reports the average and median earnings SUE for industry incumbents within a six-year period around IPO events (three years before and three years after IPO events). Results in Table 11 indicate that average earnings surprises of industry incumbents decline after large IPOs in the same industry. For example, unexpected EPS after special items (*SUE2*) is on average 1.43% (median 0.16%) before IPOs and declines to -1.05% (median 0.107%) after IPOs. The differences in both median and mean are significant. *SUE3*, which captures the unexpected earnings from analyst expectations, exhibits a relatively weak but still significant decline.

In Table 11, Panel B, we estimate a regression of the three earnings surprises measures on the IPO indicator. The IPO indicator variables load significantly negative for all three measures, even with year-quarter fixed effect in column 2 and industry fixed effect together in column 3. The estimated coefficients range from -0.0043 for *SUE3* to -0.0247 for *SUE1*, which translates into declines in unexpected earnings ranging from 0.43% (*SUE3*) to 2.47% (*SUE1*), a more than 40% decrease when compared to the pre-IPO level. Overall, the results in this section show that persistent cash flow shocks are not the reason why industry incumbent firms exhibit positive stock returns after large IPO events.

Table 11. Earnings surprises and IPO

Panel A: Quarterly earnings surprises around IPOs				
		SUE1	***SUE2***	***SUE3***
Before IPO	mean	0.061%	1.430%	-0.108%
	median	0.160%	0.160%	0.047%
After IPO	mean	-3.670%	-1.050%	-0.457%
	median	0.100%	0.107%	0.045%
DIFF	t-stat	4.98	2.21	1.94
	Wilcoxon	<0.0001	<0.0001	0.0373
Panel B: Regression of earnings surprises on IPO indicator				
		SUE1		
IPO		-0.0373	-0.0337	-0.0247
		-2.62	-1.92	-2.55
R^2		0.0001	0.0002	0.0015
Industry fixed effect		no	no	yes
Time fixed effect		no	yes	yes
		SUE2		
IPO		-0.0248	-0.0232	-0.0226
		-2.21	-2.06	-1.9
R^2		0.0001	0.0002	0.0014
Industry fixed effect		no	no	yes
Time fixed effect		no	yes	yes
		SUE3		
IPO		-0.0035	-0.0037	-0.0043
		-1.98	-2.04	-2.13
R^2		0.0001	0.0008	0.0049
Industry fixed effect		no	no	yes
Time fixed effect		no	yes	yes

Notes: The table examines the relationship between earnings surprises of industry incumbents and IPO events. SUE1 is computed as: $SUE1_{i,t} = \frac{(E_{i,t} - E_{i,t-4})}{P_{i,t}}$, *where* $E_{i,t}$ *represents EPS before extraordinary items for firm i in quarter t;* $E_{i,t-4}$ *represents EPS before extraordinary items in the previous year; and* $P_{i,t}$ *is the stock price at the end of the quarter. We adjust for earnings of special items in the computation of SUE2. Specifically, following Bradshaw and Sloan (2002) and Livnat and Mendenhall (2006), we subtract from EPS the amount of special items times 65% divided by the number of shares used to calculate earnings per share. SUE3 is calculated as the differences between actual and analyst-expected EPS, scaled by price. Panel A documents the mean and median earnings surprises around IPO events: three years before and three years after IPO events. Panel B represents the estimated results of regressing earnings surprises on the IPO indicator variable, where IPO indicator is set to be 1 for a firm-year observation if a large IPO event happened in the same industry as the specified firm i within 36 months before IPO month; otherwise, IPO is equal to 0.*

6. CONCLUSION

In this study, we analyze how large IPO events affect industry incumbents. We provide evidence that incumbents experience significant price declines around successful large IPO events due to competitive shifts. At the same time, incumbent firms' operating performances such as ROA and asset growth decline compared with their pre-IPO level. But despite these declines, incumbent firms earn positive abnormal returns within three years after these large IPO events; in other words, incumbent firms' cost of equity increases in the long run. Their default probability also increases.

To verify our risk explanation, we first show that incumbent firms' operating performance declines and their default probability increases. Our IPO indicator has significant explanatory power for incumbent firms' likelihood of involuntary delisting. We use the ICAPM model to provide evidence that incumbent firms' stock returns exhibit pro-cyclical patterns, meaning their stocks will generate lower returns during the economic downturn. Such features will increase investors' risk exposure. After IPO events, incumbent firms' stock returns become even more sensitive to economic conditions (i.e., more procyclical), indicating that these stocks become riskier after large IPO events. Investors thus would require even higher returns as compensation for increased risk.

We further investigate if the increased risk for incumbent firms is attributable to IPO-related competitive advantages. We propose that if enhanced competition increases incumbent firms' risk, increases in their returns should be greater for industries where IPO-related competitive advantages are stronger. Using cross-sectional tests, we provide some evidence that increases in incumbent firms' expected returns are greater for firms in industries with low differentiability, a large number of public firms, and a smaller market size. These findings suggest that large IPO events can increase the risk to industry incumbents by exerting competitive pressure. We fail to find a relationship between industry concentration and increases in incumbent firms' returns, probably because industry concentration could imply either stronger or weaker competition (Karuma, 2007).

Last, to rule out the potential argument that the positive abnormal returns we observed for incumbents are attributable to persistent positive cash flow shocks within three years after the large IPO events, we examine earnings surprises and unexpected profitability for incumbent firms before and after IPO events in the industry. In fact, incumbent firms' earnings surprises become negative rather than positive after large IPO events, confirming that the abnormal returns we observe for incumbent firms are not from persistent positive cash flow shocks.

The current study supplements previous studies regarding IPO-related competitive advantages by documenting that incumbent firms' default probability, operating performances, and cost of equity increase after large IPO events in the industry. Such competitive advantages are more significant for industries with lower product differentiability, smaller market size, and a large number of firms. The limitation of the paper lies in the measure of cost of equity. In general, the *ex-ante* cost of equity will be better compared with the *ex-post* realized cost of equity we use in the paper. However, to estimate ex-ante cost of equity, we need to not only make assumptions about future growth rate, growth horizon, and so forth but also estimate future earnings using either analyst forecasts which would then significantly reduce our sample or earnings prediction models which would involve model specification issues. In the current context, realized returns better reflect firms' realized cost of capital and include more practical insights for industry practitioners. Future researchers can focus on the channels through which such competitive effects occur.

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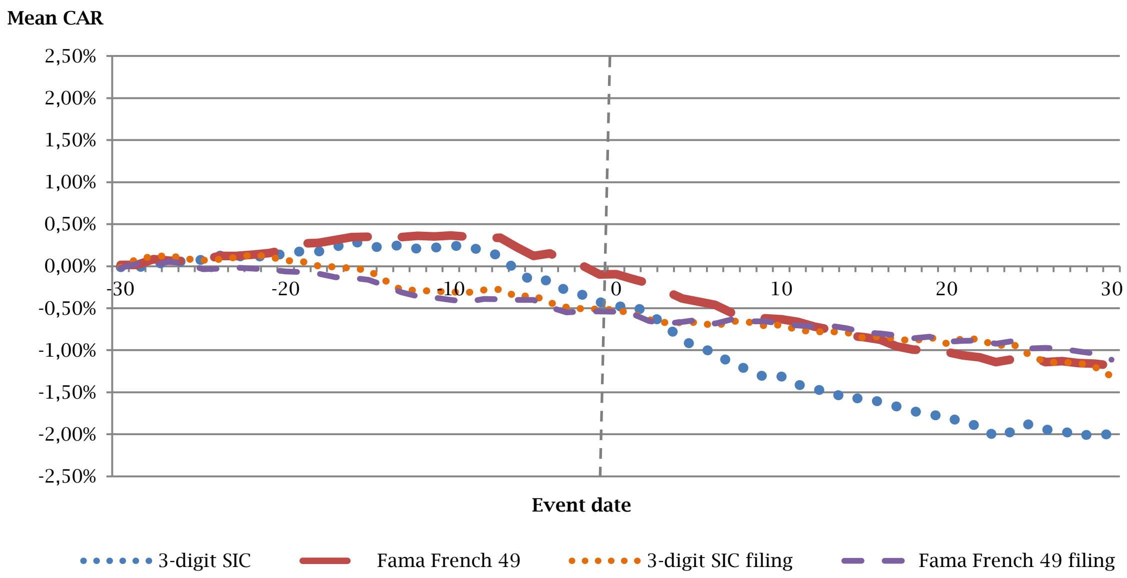
APPENDIX

Table A.1. Calendar time abnormal return for incumbent firms

	Calendar-time portfolio				*Robustness-CTAR*			
	CAPM	*Fama-French 3-factor*	*Fama-French 4-factor*	*Fama-French 5-factor*	*CAPM*	*Fama-French 3-factor*	*Fama-French 4-factor*	*Fama-French 5-factor*
alpha	0.764%	0.532%	0.652%	0.545%	0.788%	0.659%	0.706%	0.678%
t-stat	2.40	2.70	3.58	3.01	2.85	3.84	4.86	3.97

Figure A.1. Incumbents' cumulative abnormal returns around IPO completion and filing



Notes: IPO firms are selected according to their proceeds. We only select IPOs that have the largest proceeds in their industry at the IPO year. Industries are defined using three different criteria: 3-digit SIC code, 2-digit SIC code, and Fama-French 49 industry. Incumbent firms are defined as existing public firms in the same industry as the IPO firm at the time of the IPO. We further require incumbent firms to be publicly tradable at least three years before the IPO year. Our sample of incumbent firms included 37,768 incumbent firm-year observations corresponding to 1177 IPOs using 3-digit SIC code, and 64,585 incumbent firm-year observations corresponding to 563 IPO events using Fama-French 49 industry. Average daily cumulative abnormal returns are shown on the y-axis, calculated as the equally weighted mean market model adjusted return across all incumbent firms. The x-axis shows the timeline in days around an IPO event, where day 0 represents the IPO date.