How IPO firms' product innovation strategy affects the likelihood of post-IPO acquisitions?**

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Abstract

This study investigates why newly listed firms become M&A targets shortly after their initial public offering (IPOs) from the perspective of product innovation. We find strong empirical evidence that IPOs with less established trademarks increase the likelihood of becoming IPO targets. We also find that the negative relation between established trademarks and the likelihood of becoming IPO targets is more pronounced in highly competitive industries and is primarily driven by the M&A supply side. IPOs with more established trademarks can fend themselves against the product market race as independent firms. They can meanwhile realize superior post-IPO financial as well as innovation performance. To acquire such firms, acquirers need to offer substantially higher takeover premiums. However, some empirical evidence suggests that less product innovation-intensive IPOs tend to deliberately seek potential acquirers to support their product market competing position and therefore are more likely to initiate an M&A deal shortly after going public.

Keywords: Product Innovation; Trademarks; IPO; M&A

JEL Classification: G23, G32, G34, O34

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1. Introduction

Why do a significant portion of newly listed firms become M&A targets shortly after their initial public offering (IPOs)? According to the existing literature, Ciccotello et al. (2001) report that 36% of mutual thrift IPOs are acquired within five years after going public. De and Jindra (2012) and Chemmanur et al. (2019) also indicate that around 15-20% of newly listed firms become acquisition targets within three years of their IPOs.

Even though these rates are not relatively high, the phenomenon involving IPO targets becomes more striking than seasoned acquisition targets. Surprisingly, we notice that IPO targets take up to more than half of all M&A targets (58.21%) within a ten-year period.[1] Meanwhile, the value of IPO targets accounts for 50.81% of the total value of the M&A market within the same horizon. These acquisitions that happened so promptly following the IPO seem to challenge the traditional view that the IPO is the natural end-state of successful startups (Ragozzino and Reuer, 2007). Why an M&A occurs immediately after an IPO remains an important but less explored question in the academic literature. Specifically, do post-IPO acquisitions stem from IPOs' intention to certify their value for potential buyers (Zingales, 1995) and IPOs' success (Jain and Kini, 1999 and De and Jindra, 2012) of being attractive targets, or from their weakness of looming insolvency (Hensler et al., 1997 and Tsoukas, 2011) to seek buyers to support their post-IPO growth? Furthermore, no study has yet examined this puzzle from the product market competition perspective.

Anecdotal evidence from media news seemingly suggests that product market competitiveness may relate to this puzzling phenomenon. PayPal was a fast-growing startup that went public in

[1] We confirm the fate of newly listed firms up to their tenth anniversary and consider firms as seasoned targets if they are acquired after three years and within a ten-year horizon.

February 2002. However, shortly after PayPal's public venture, its CEO, Peter Thiel, initiated a merger negotiation with eBay and was successfully acquired by eBay only a half-year after the IPO. Financial analysts felt the deal was quite puzzling and had more mixed reviews toward it. Specifically, an analyst from a market research firm, Celent Communications, could not understand why PayPal chose not to remain independent and leave the stock market so quickly. However, the CEO of PayPal defended his choice and believed that integrating with eBay could support its competitiveness and future growth (*The New York Times*, 2002). In this case, it is worth noting that PayPal does not have any registered trademarks prior to its IPO. Another surprising case is Kayak, an online travel agency and metasearch engine that went public in 2012. Analysts at that time indicated that given Kayak's market leadership and consumer momentum, there would be tremendous demand and healthy profitability levels for Kayak as a public firm (*Investors Business Daily*, 2012). However, Kayak was sold to Priceline.com before its first anniversary on NASDAQ (*Wall Street Journal*, 2012). Surprisingly, even though Priceline.com was not an active acquirer and had so far only acquired four targets, the deal was solicited by the acquirer, Priceline.com. According to Priceline.com, they acknowledged the attractive value of Kayak's established brands. Priceline.com also guaranteed that Kayak could still operate independently even after the transaction (*TechCrunch*, 2012). Interestingly, Kayak owned 18 established trademarks prior to its IPO.

To thrive in the competitive product market race and cater to consumers' growing demand, companies dedicate themselves to creating and developing new products. In doing so, firms can distinguish themselves from their industry rivals and therefore are rewarded by superior growth opportunities and better financial performance through product innovation (see e.g., Baker and

Hart, 2007; Porter, 2008).[2] In this study, we are interested in finding out whether product innovation is associated with an IPO firm's growth pathways, between growing organically as independent firms or integrating with established firms via M&A to seek a superior product market position.

To effectively proxy for product innovation, we follow the official definition of product innovation given by the Organization for Economic Co-operation and Development (OECD) and consider trademarks that are available from the United States Patent and Trademark Office (USPTO)[3]. In line with Hsu et al. (2021b), given the unique insights that USPTO trademark data can provide, USPTO trademark data is superior to other measures related to new product development used in prior studies, such as new products described in firms' 10-K reports (Hoberg and Phillips, 2010); new product announcements from media news (Mukherjee, Singh, and Žaldokas, 2017); retail sales data such as Nielsen's Retail Scanner data (Argente et al., 2020 and Aparicio, Metzman, and Rigobon, 2021), as well as survey data from *Consumer Reports* magazine. Specifically, compared to those abovementioned proxies, USPTO trademark data has several advantages (Hsu et al., 2021b). First, USPTO trademark data is publicly available and covers a long period that enables us to track all newly developed products back to the 1970s and perform large-scale empirical analysis. Second, the trademark coverage in USPTO is comprehensive and covers trademark registrations from both public and private firms, small and

[2] The importance of product innovation is also supported by several anecdotal evidence. According to the 17th Annual Global CEO survey from Price Waterhouse Coopers conducted in 2014, CEOs from almost all industries rank product innovation among the top issues and believe it is one of the most important forces of driving firms' long-term growth (Faurel et al., 2020). Interestingly, some CEOs even prioritize product innovation over increasing market share, as they believe new product development itself guarantees their market competitiveness and will eventually enhance existing market shares in the long run.

[3] The OECD defines product innovation as the introduction of goods or service that is newly or significantly improved. Based on existing literature in economics, product innovation is also measured by trademarks, as trademarks reflect the commercialization of newly developed goods or services (see e.g., Lev, 1999; Mendonça, Pereira, and Godinho, 2004; Sandner and Block, 2011). Although trademark is just a sign (word, logo, phrase, etc.), it effectively differentiates a firm's unique goods or services from its industry peers (Landes and Posner, 1987; Besen and Raskind, 1991; Chemmanur et al., 2020).

major product lines, and all product/service categories (industrial as well as consumer products/services). Third, USPTO trademark data does not suffer from biases associated with firms' strategic disclosures in their financial reports, firms' marketing strategies, and media coverage preferences. Overall, we believe that trademarks are effective and reliable measures for product innovation.

Indeed, industries recognize the important value of trademarks. Faurel et al. (2020) document a survey called "Business Research and Development and Innovation Survey" which is conducted by The Census Bureau and National Science Foundation. By including more than 45,000 U.S. firms, the survey suggests that among several industries, approximately 60% of U.S. firms name trademarks as the crucial innovation output while 41% rank utility patents as the critical innovation output. Unlike patents which represent the output of technological innovation, trademarks reflect the output of product innovation. Nonetheless, the finance literature has not sufficiently examined product innovation (trademarks), while a large but growing string of literature on the relation between corporate finance and innovation only restricts the focus on technological innovation (patents).

We argue that trademarks as the output of product innovation better represent a firm's product market competitiveness as well as the viability of its business, compared to patents as technological innovation. Firstly, as suggested by Katila (2002) and Mendonça, Pereira, and Godinho (2004), technological innovation (patents) cannot directly transform into enhanced firm value until patents have passed the commercialization process. Conversely, trademarks carry on the end-state commercial value from corporate innovation, as customers can directly recognize the newly developed final products through successfully resisted trademarks. Secondly, although a large number of corporate innovation studies has demonstrated that corporate patenting activities contribute to firm performance, Hirshleifer, Hsu, and Li (2013, 2018) and Hsu et al. (2021a) illustrate that it is quite difficult for stock investors to process patent-related information as there is a long way between technological innovation output (patents) and successful final products (trademarks) with meaningful commercial value. Hsu et al. (2021a) also point out that patents do not necessarily define a firm's success because it is highly uncertain whether positive future cash flows can be realized from patents. It is trademarks rather than patents, that are associated with significant abnormal returns. On the relation between corporate innovation and the likelihood of M&As, Bena and Li (2014) find that firms with low-level technological innovation output (patents and patent citations) tend to be acquisition targets. Conversely, Wu and Chung (2019) find that for mature firms, technologically innovative firms (higher cumulative number of patents) increase their likelihood of becoming acquisition targets. However, given the shortcomings of patents, trademarks may represent the whole picture of product market competitiveness.

Chemmanur et al. (2019) established a theoretical framework to investigate the post-IPO growth options of IPOs from the perspective of product market competition. They postulate that whether an IPO firm has an established viable business mode to fend itself against product market competitiveness is significantly associated with its post-IPO growth options. Their model posits two compelling outcomes. On the one hand, IPOs that are more viable in the product market are more likely to be acquired shortly after the IPO. They can easily draw the attention of acquirers, and the synergies generated from such acquisitions are higher. On the other hand, they note that if an IPO firm is sufficiently viable against fierce product market competition, it prefers to grow as an independent firm. Its management is sufficiently confident of fending off product market race. Their following empirical analysis on European IPOs is in line with the first scenario.

European IPO firms with high product market viability (measured by sales growth and growth opportunities) are more likely to be acquired within three years after the IPO.

Nonetheless, we argue that established product innovation output may better capture IPO firms' product market viability compared to proxies of operating performance. The value of operating performance can be realized relatively quickly while product innovation is a long-term commitment. Its benefits also tend to be realized over a long period of time (Holmstrom, 1989, Griliches, 1992 and Hall, 1996). Moreover, existing studies suggest a significant relationship between innovation and product market competition. Porter (1992) shows that innovation contributes to firms' long-term growth and competitive advantage. Aghion et al. (2005) find a significant and positive relationship between product market competition and innovation for neck-and-neck firms. Schweinbacher (2008) finds that innovation can significantly differentiate a firm's products from its competitors, and those with innovative products are more able to succeed in the face of market competition. Based on a real option model, Gu (2016) finds a significant interaction between firms' engagement in innovation and market competition and that innovation intensive firms obtain higher returns in industries with a higher degree of product market competition. Therefore, in this study, we assume that product innovation is an essential factor that must be considered to better understand the effect of product market competitiveness on newly listed firms' growth pathways. Using product innovation (trademarks) could more effectively and accurately capture the product market competitiveness than proxies as operating performance or patents.

We consider a sample of IPO firms between 1980 and 2013 and calculate different proxies for established product innovation prior to the IPO. We find that product innovation intensive IPO firms are more likely to grow organically as independent firms, whereas less product innovation intensive IPO firms are more likely to become acquisition targets. One-unit increase in established trademarks prior to going public is associated with a decrease in the likelihood of becoming IPO targets by 37.83% (75.46% compared to our matched sample using propensity score matching routine). Our baseline results remain robust after a rich set of robustness tests. Furthermore, to overcome the potential issue of endogeneity between product innovation and the likelihood of becoming IPO targets, we first use an exogenous source as an instrumental variable (IV), namely, the leniency of trademark examining attorneys (see e.g., Hegde and Raj, 2019; Sampat and Williams, 2019; Chemmanur et al., 2020; Farre-Mensa, Hegde, and Ljungqvist, 2020; and Melero, Palomeras, and Wehrheim, 2020). We then implement two quasi-natural experiments using the *1996 Federal Trademark Dilution Act* and the decision of U.S. Supreme Court in 2003 (*Moseley v. V Secret Catalogue, Inc.*) to perform the difference-in-differences (DID) analyses (Heath and Mace, 2020). The results from the IV estimation as well as the DID analyses confirm our baseline finding.

To identify the channels through which product innovation affects an IPO firm's likelihood of getting acquired, we first find that established trademarks significantly enhance nascent firms' product market competitiveness. Our baseline results become even more pronounced in highly competitive industries, suggesting that stronger product market competitiveness increases nascent firms' capability to grow independently while decreasing the likelihood of becoming IPO targets. Next, we examine whether growing organically as independent firms is the right option for production innovation-intensive firms. We find that independent IPOs with more established trademarks are associated with superior post-IPO financial/operating and innovation performance. Furthermore, we investigate whether an acquisition shortly after the IPO is driven by the demand side or supply side. We find some evidence that IPOs with weaker product market competitiveness are more likely to initiate an acquisition. Finally, we examine the impact of product innovation on takeover costs. We find that acquirers have to offer IPO targets sufficiently high financial compensation to entice an IPO firm into accepting an M&A agreement. A one-standard-deviation increase in trademark raises the takeover premium by 14%, equivalent to a $141.87 thousand increases in the aggregate dollar amount.

Our research makes several contributions to the literature. First, we provide new insights and explanations related to a less explored research question on why a significant portion of newly listed firms promptly become M&A targets. We are the first to document that product innovation (trademarks) is closely related to the likelihood for an IPO firm of getting acquired shortly after the IPO. We then suggest that established output from newly launched product innovation can predict the choice of two alternative post-IPO growth pathways of startups: growing organically as independent firms or integrate with well-established companies to support their growth. Second, our study enriches the new but growing strand of research on trademarks and corporate financing activities (see e.g., Chemmanur et al., 2020; Faurel et al., 2020; Heath and Mace, 2020; and Hsu et al., 2021a and 2021b). Third, our research complements previous studies focusing on M&A initiations. Prior studies assume that M&A deals are initiated by potential bidders (Fidrmuc and Xia, 2017) and retain the target's financial weakness as a potential explanation for the initiation of the M&A (Masulis and Simsir, 2018). We extend this literature by demonstrating that the lack of product market competitiveness (innovation) could also motivate the initiation of an acquisition for IPO firms.

The remainder of this paper is organized as follows. Section 2 introduces the data, sample, and univariate analysis. Section 3 presents the multivariate regression analyses. Section 4 addresses the endogeneity concerns. Section 5 provides additional robustness checks. Section 6 reports further analysis and Section 7 concludes the paper.

2. Data and sample

2.1. Sample construction

Our initial sample consists of U.S. IPOs completed between 1980 and 2013,[4] which are collected from the Thompson Reuters' Securities Data Corporation (SDC Platinum) New Issues database. Following the IPO literature, we exclude IPOs with offer prices that are unknown or less than $5 in the SDC; we also exclude IPOs that are identified as American depositary receipts (ADRs), closed-end funds, foreign issues, real estate investment trusts (REITs), reverse leverage buyouts (LBOs), spinoffs, and unit offerings. Moreover, we only include IPOs that are publicly traded on the NYSE, AMEX, or NASDAQ stock exchanges. We next move to the collection of data related to IPOs, ending up with acquisition targets. We also retrieve these data from the SDC Mergers & Acquisitions database. To identify IPO targets, we confirm whether an IPO firm becomes an acquisition target or remains an independent firm within the three years that follow the issuing year (see, e.g., Field and Karpoff, 2002; De and Jindra, 2012; Chemmanur et al., 2019).[5] We only consider acquisitions with deals valued at $1 million or higher and acquisitions with over 50% of the IPO target's equity. Furthermore, we confirm the CRSP's delisting codes and exclude firms delisted for reasons other than those related to the M&A, given our focus on the likelihood of becoming IPO targets. Following the IPO literature, we exclude the financial firms. We also exclude deals made by acquirers in the financial industry, given that they do not reflect the relation between product innovation and market product competition. After these data screening processes, the initial sample contains 4,596 IPOs established between 1980 and 2013,

[4] Our sample also stops in 2013, since we intend to confirm whether an M&A occurred within the three years following the IPO. In addition, scaling the number of citations per patent requires a five-year time horizon.

[5] Moreover, following the IPO literature on post-IPO M&A activities (see e.g. Celikyurt et al., 2010, and Boulton, 2011), we also use the time period of five years after the IPO, and our empirical results remain qualitatively unchanged.

521 of which experience a trade sale. We observe that a non-trivial portion of IPOs become acquisition targets within three years after going public, especially in the 1990s, consistent with the ratio reported by De and Jindra (2012). Overall, the percentage of IPO targets is 11.34% of all IPO firms between 1980 and 2013, as shown in Panel A, Table 1. However, the percentage of IPO firms becoming acquisition targets is around 15% after the 1990s. Although this percentage between 10% and 15% is not considered very high, compared to total IPOs, we note that more than half of all M&A targets are IPO firms (58.21%). Also, the value of M&A for IPO targets represents 50.81% of the entire M&A value within a ten-year period (see Panel B, Table 1).

Panel C in Table 1 presents the industry distribution of all IPO firms and IPO targets classified by the 49 Fama-French industries. We can see that IPO targets are across a wide range of industries, and significantly more IPO firms tend to become IPO targets in high technology-related industries.

—Please insert Table 1 about here—

2.2. Measuring product innovation

Previous studies show that trademark is a reliable measure of product innovation (Lev, 1999, Mendonça, Pereira, and Godinho, 2004; Sandner and Block, 2011; Chemmanur et al., 2020; Faurel et al., 2020; Heath and Mace, 2020; Hsu et al., 2021a and 2021b). In addition, Chen, Hsu, and Wang (2021) further confirms trademarks can effectively measure product innovation. Specifically, they use product-related patents as the proxy of product innovation and find that such patent-based measures produce qualitatively similar empirical results as trademarks. The data pertaining to trademarks are collected from the Trademark Case Dataset, which is available at USPTO's website (the United States Patent and Trademark Office). In the Trademark Case Dataset, there is information on 9.1 million trademark applications and registrations in total, starting from 1870 to the present. Specifically, the database includes detailed information on trademarks' classification, filing date, ownership, registration, the names of the attorneys who review and make registration decisions on trademark applications, and examining attorneys who examine the trademark applications from the database. Following the studies mentioned above, we only consider successfully registered trademarks. To link IPO firms and trademark data, we employ a fuzzy matching algorithm to merge IPO firms with trademark data. Also, we manually calibrate each match to ensure the accuracy of the matching process.

With these collected trademark data, we create the baseline measure for product innovation with the natural logarithm of successfully registered trademarks prior to the IPO stage (Chemmanur et al., 2020): *Ln(1+Trademark)*. Other than the simple trademark counts, to capture the quality of trademarks, we follow Hsu et al. (2021) to create additional five proxies for product innovation: *Ln(1+Diversity), Ln(1+Exploitation), Ln(1+Exploration), Ln(1+Marketing),* and *Ln(1+Product)*. Detailed variable definitions related to the six measures for product innovation are documented in Table A1, Appendix A.

2.3. Control variables

Following the IPO and M&A literature (Ambrose and Megginson (1992); Berger et al., (1996); Harford (1999); Harford (2005); Wang and Xie (2008); Baker (2012), De and Jindera (2012); Bena and Li (2014); Offenberg and Pirinsky (2015); Masulis and Simsir (2018); and Chemmanur et al. (2020)), we consider the following control variables: advertising expenses (*Advertise*), the number of years between the establishment year and the IPO year (*Age*), the buy-and-hold stock returns (*BHAR*), the cash ratio (*Cash ratio*), Herfindahl-Hirschman Index (*HHI*), the gross proceeds from IPO (*IPO proceeds*), the financial constraint (*KZ index*), leverage (*Leverage*), the asset liquidity (*Liquidity*), the industry merger wave (*M&A activity*), research and development expenses (*R&D*), the technological innovation outputs (*Ln (1+Patents)*), the return on assets (*ROA*), the sales growth rate (*Sales growth*), the firm size (*Size*), the growth opportunities (*Tobin's q*), the underwriter rank (*Underwriter*), and indicators of whether an IPO is backed by venture capital (*VC*). The variable definitions are provided in detail in Table A1 of Appendix A.

2.4. Univariate analysis

Table 2 reports summary statistics comparing the characteristics of the independent IPOs to IPO targets for the period from 1980 to 2013.[6] We find that IPO targets tend to be younger and spend less on advertisements while having better operating performance (higher cash ratio, less information asymmetry, more asset liquidity, more growth opportunities, and lower leverage). In addition, IPOs that operate in more competitive industries, managed by more reputable underwriters, and VC backed are more likely to be taken over shortly after the going public stage. Further, newly listed firms are more likely to become acquisition targets during merger waves.

—Please insert Table 2 about here—

3. Empirical results

3.1. Baseline results

To empirically test the likelihood that an IPO firm becomes an IPO target, we employ a logit regression using a cross-sectional dataset from the fiscal year immediately preceding the actual year during which an M&A occurs (for independent IPOs, the measures are taken from the third fiscal year). Note that the six measures for innovation, *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*, are computed based on the fiscal year immediately preceding the IPO year.

[6] As we consider a large set of control variables, we compute a correlation matrix that confirms the absence of multicollinearity. For brevity, correlation results are not reported but are available from the authors upon request.

$$IPO\ targets \binom{1}{0}_{i,t} = \alpha + \beta_1 \cdot Product\ innovation_i + \nu_n \cdot N_{i,n,t-1} + \varphi_k + \varphi_t + \varphi_s + \varepsilon_{i,t} \quad (1)$$

where *IPO targets* is a binary variable that equals 1 if an IPO firm gets acquired via the M&A within three years after going public and is 0 otherwise. *Product innovation* is measured by the above-mentioned six variables: *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*. N_n is a vector of the firm-specific characteristics; φ_k is the industry fixed effects; φ_t is the year fixed effects; and φ_s is the state fixed effects.[7]

Panel A of Table 3 presents the results of the logit regression using cross-sectional data. Our baseline results show that IPO firms that launched their product innovation before going public are more likely to grow as independent firms and are less likely to become acquisition targets. The coefficients of product innovation's proxies are statistically significant at the 1% or 5% level, except the proxies of exploitation trademarks and marketing trademarks. The results also have economic significance. For instance, in Column 1, the coefficient of the aggregate quantity of trademarks an IPO firm has prior to going public is -0.475, which is statistically significant at the 1% level. This result is also economically significant; a one-unit increase of *Ln (1+Trademark)* is associated with a decrease in the likelihood of becoming IPO targets of 37.83%.

As for exploitation trademarks, it is plausible that IPO firms are too young to generate sufficient exploitation trademarks to affect their market competitiveness significantly. Note that exploitation trademark is defined as trademarks that a firm has already registered at least one trademark in this trademark's class (assigned by the USPTO) over the last 10 years. As for marketing trademarks, it is not surprising that this proxy is not significant. It indirectly shows that it is the "real" product innovation that increases the product market competitiveness as

[7] We control the state fixed effects, given Boulton (2011)'s finding that the likelihood that a firm will be acquired shortly after the IPO is related to anti-takeover provisions at the state level.

independently growing companies, not the flamboyant and superficial marketing tricks. Moreover, we also employ a panel logit regression to capture the dynamics of entrepreneurial firms' post-IPO financial and operating performance. The control variables related to financial and operational performance are measured dynamically based on different fiscal years. From Panel B, we observe that the empirical results are highly consistent with those based on cross-sectional data. We consistently find that the likelihood of ending up with IPO targets is negatively related to more established product innovation. We interpret these results as strong support for our main hypothesis.

For the control variables, we find that startups' superior post-IPO operating performance draws the attention of acquirers. These results mirror those of De and Jindra (2012). Specifically, IPO targets are associated with younger firm age (*Age*), higher stock performance (*BHAR*), and asset liquidity (*Liquidity*). Moreover, we find that larger (*Size*) are less likely to become acquisition targets. As expected, larger firms are more able to fend for themselves as independent firms. In addition, our empirical evidence suggests that IPOs operating in highly competitive industries (*HHI*) are more likely to experience sell-outs since it tends to be more difficult for them to fend themselves against fierce product market competition. Furthermore, consistent with Ragozzino and Reuer (2007), we find that IPOs raising higher gross proceeds and those managed by more reputable underwriters are more likely to be acquired, as such firms have less information asymmetries. Interestingly, we find that firms with less technological innovation (patents) are more likely to become acquisition targets, consistent with Bena and Li (2014) finding for matured firms.[8]

—Please insert Table 3 about here—

[8] In addition to the logit model, we re-estimate the baseline results using linear probability models as a robustness check. The results (reported in Table A4 in the Appendix) are highly consistent with our baseline results from the logit model.

3.2. Results from the Cox hazard model

The multivariate logit regression analysis fails to consider the duration between a firm's public listing and becoming IPO targets. In other words, the logit estimation treats an IPO target that happened in the first post-IPO year in the same manner as the one that became an acquisition target in the third post-IPO year. Thus, we employ the Cox hazard model (counting process), which permits the control variables to change over time and multiple measure intervals prior to the censoring event (Cox, 1972; Andersen and Gill, 1982). The Cox hazard model estimates the conditional probability that an event will occur, given that it has not yet happened. Positive (negative) coefficients indicate that the covariate accelerates (decelerates) the time to the event. The hazard event refers to the circumstance in which an IPO is acquired within three years after going public. We also report the hazard ratio. A hazard ratio equal to one means that an independent variable neither increases nor decreases the probability that the event will occur. A hazard ratio greater (smaller) than one suggests that an independent variable increases (decreases) the probability that the event will occur. We estimate the Cox hazard model as Equation (2): where $h_0(t)$ is the hazard function, and the dependent variable is the hazard ratio relating to the event of becoming IPO targets. Product innovation is measured by the above-mentioned six proxies: *Ln (1+Trademark), Ln(1+Diversity), Ln(1+Exploitation), Ln(1+Exploration), Ln(1+Marketing),* and *Ln (1+Product)*. N_n is a vector of the firm-specific characteristics; φ_k is the industry fixed effects; φ_t is the year fixed effects, and φ_s is the state-fixed effects.

$$\hbar\ (t) = \hbar_0(t)\exp\left[\beta_1 \cdot Product\ innovation_i + \nu_n \cdot N_{i,n,t-1} + \varphi_k + \varphi_t + \varphi_s\right] \quad (2)$$

Table 4 presents the results from the Cox hazard model. Overall, we confirm our baseline results. All our trademark proxies (except exploitation trademarks and marketing trademarks) are negative and statistically significant at conventional levels, suggesting that an IPO firm's established product innovation significantly decreases the probability of getting acquired shortly after public listing. Our results confirm that product innovation decelerates the time in which newly listed firms turn into IPO targets.

—Please insert Table 4 about here—

3.3. Results of propensity score matching

One potential issue with the previous results is that trademarks cannot be randomly distributed across all IPOs. For example, larger, more profitable, and VC-backed startups could be more capable of engaging in innovation activities. To control for a potential self-selection bias, we follow Malmendier and Tate (2009). We first run a probit regression for our IPO sample to predict the "IPO targets" based on a set of firm-specific characteristics (see Table A2, Appendix A for the probit regression results). The dependent variable is a binary variable that equals one if an IPO firm becomes acquisition targets within three years after the IPO and zero otherwise. Second, we regress the IPO targets indicator on the vector of control variables. The fixed effects for the year, industry and state are included. We then use the probit regression's predicted values to construct a nearest-neighbor matched sample for IPO targets. For each year, we choose (without replacement) the independent IPOs with the propensity scores closest to those of each IPO target. We call these samples the "predicted" IPO targets.[9]

Table 5 reports the results of the post-matching analysis. We find that all product innovation's proxies (other than marketing trademarks) remain negative and statistically significant at the 1% level, suggesting that IPO firms with established product innovation are less likely to become IPO targets. The coefficient of our baseline measure, *Ln(1+Trademark),* is -1.405, which is statistically significant at the 1% level. With regard to the economic significance, a one-unit

[9] As an alternative to the propensity score matching technique, we also consider the Heckman procedure to correct for a potential selection bias. These results are not reported but are highly consistent with those derived using the propensity score matching technique and are available upon request.

increase of *Ln(1+Trademark)* is associated with a decrease in the likelihood of getting acquired of 75.46% compared to the matched sample. Thus, the PSM analysis further confirms that firms with higher viability in terms of product market competition are more able to fend for themselves. These firms are more likely to grow organically while are less likely to become IPO targets.

—Please insert Table 5 about here—

4. Endogeneity concerns

4.1. Instrumental variable analysis

The above empirical evidence illustrates that a higher level of established product innovation is associated with a lower likelihood of becoming acquisition targets for newly listed entrepreneurial firms. It is, however, important to examine the direction of the causality between product innovation and the likelihood of getting acquired. Our empirical results could be driven by other factors not included in our analysis and related to both trademarks and the IPO firms' probability of getting acquired. Trademark applications could also be endogenous, as applying trademarks is a firm's subjective choice (Chemmanur et al., 2020). To address the above endogeneity concerns, we select an instrumental variable (IV) related to product innovation but exogenous to the likelihood of becoming IPO targets. Following Chemmanur et al. (2020), Farre-Mensa, Hegde, and Ljungqvist (2020), Melero, Palomeras, and Wehrheim (2020), Hegde and Raj (2019), and Sampat and Williams (2019)[10], we choose to employ the trademark reviewing attorneys' leniency (approval rate of trademark applications) to perform our instrumental variable (IV) analysis. Specifically, we first compute a trademark attorney's leniency (rate of approval) for trademark applications. The equation for computing the time-varying leniency of an individual attorney is formulated as:

[10] They use the average examiner leniency of patent applications as an IV for technological innovation analysis.

$$Individual\ Leniency_{i,j,k,t} = \frac{Registration_{j,t} - Registration_k}{Application_{j,t} - 1} \quad (3)$$

where $Individual\ Leniency_{i,j,k,t}$ denotes the trademark approval rate of an attorney j for trademark application k submitted by firm i in year t. $Registration_{j,t}$ and $Application_{j,t}$ are the numbers of trademark successfully registered and total trademark applications examined, respectively, by trademark attorney j in the same application year as application k. $Registration_k$ indicates the outcome of an application k and takes the value of one if the application is approved and zero if rejected.

To further construct our IV for the quantity of successfully registered trademarks, we calculate the mean value of the trademark attorneys' leniency across all submitted trademark applications. We average examiner leniency across applications. Specifically, we calculate the mean value of trademark attorneys' leniency prior to IPO as the IV. The equation of computing the average leniency for trademark attorneys is presented as:

$$Average\ Leniency_i = \frac{1}{n_i} \sum_j Individual\ Leniency_{i,j,k,t} \quad (4)$$

where j denotes trademark attorney and n_i is the aggregate number of trademark applications submitted by IPO firm i prior to the public offering stage. Since the IV analysis involving trademark reviewing attorneys' leniency, it is only applicable for the firms with granted trademarks. We, therefore, perform the IV estimation by using our subsample for IPOs with non-zero successfully registered trademarks. Before moving to the IV regression analysis, we check whether our IV satisfies both the relevance condition and the exclusion restriction.

4.1.1. Relevance condition

We argue that if a given firm's average trademark approval rate (attorney leniency) is higher, it should have more successfully registered trademarks. Also, we check the distribution of trademark attorney's annual leniency and find that the distribution generally follows a normal distribution with sufficient variations. Specifically, the attorney's annual leniency's median value is 65.10%, while the interquartile range turns out to be 20.55%. These statistics are largely consistent with the findings of Chemmanur et al. (2020) for trademark attorney's leniency.

4.1.2. Exclusion restriction

In addition, we argue that our IV satisfies the exclusion restriction for the following two reasons. First, we believe that our IV is randomly assigned, as USPTO allocates trademark applications randomly to attorneys reviewing the applications (Graham et al., 2013). Second, firms submitting trademark applications do not know the identity of trademark reviewing attorneys prior to the release of application outcomes. In turn, it might be difficult for attorneys to subjectively influence the reviewing process and the approval rates.[11,12] Put it differently, the trademark attorneys' leniency can hardly be affected by the firm-specific characteristics.[13] Nevertheless, one shortcoming of the information on trademark reviewers is that, unlike the information on patent reviewers, the USPTO does not provide detailed information on the reviewer's seniority or experience. It is important to address this issue as there exists a learning effect for trademark reviewers.[14] Thus, following Chemmanur et al. (2020), we only include trademark attorneys who have examined a minimum of ten trademark applications in a given year. Given that in non-laboratory research, every IV could have strengths and weaknesses, we argue that, to a large extent, trademark reviewers' leniency could be considered as an exogenous source.

4.1.3. Results of the IV analysis

Table 6 reports the empirical results of the IV estimation. Since our baseline model is a logit

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[11] According to (Graham et al., 2013), the reviewing process involves some level of attorneys' discretion and trademarks that are likely to create confusion with existing trademarks tend to be turned down.

[12] It is worth noting that although the trademark system allocates trademark applications randomly, we need to acknowledge that trademark reviewers can sometimes circumvent that randomness. We thank an anonymous referee for highlighting this point.

[13] We also check the correlation between trademark attorneys' leniency and the firm characteristics in our sample and find that the pairwise correlations are very small.

[14] We appreciate this valuable comment suggested by an anonymous referee.

regression, we employ an "ivprobit" for the IV analysis. The second-stage results are documented in Table 6, with the first-stage results being reported in Table A3 in the Appendix. The first-stage estimation shown in Table A3 proves a positive and statistically significant link between established trademarks and trademark examiners' leniency, no matter which trademark proxy is used. Also, the significant Stock-Yogo Test further confirms the relevance condition. Overall, we confirm that trademark reviewing attorneys' leniency is a valid IV to a large extent. Pertaining to the results of the second-stage estimation, we can see clearly in Table 6 that the negative effect of product innovation on reducing IPO firms' likelihood of getting acquired becomes even stronger than the baseline estimation. The coefficients of all the six measures of product innovation are negative and statistically significant at the 1% level. Hence, we conclude that after addressing the endogeneity issue, the results of our IV analysis confirm our baseline results. IPOs that have been successful on product innovation prior to going public are more likely to grow organically as independent firms and are less likely to become IPO targets.

—Please insert Table 6 about here—

4.2. Quasi-natural experiment

So far, our IV approach, to a large extent, captures the exogenous portion of the causal link between product innovation and the likelihood of becoming IPO targets. However, we have to acknowledge that the selected IV could be questionable. To further deal with the identification, an exogenous shock is required. Accordingly, we adopt two quasi-natural experiments. The first one involves the *1996 Federal Trademark Dilution Act* (FTDA), which became the federal law of the U.S. on January 16th, 1996. The FTDA aims to offer stronger protections for famous trademarks from improper uses that can dilute their distinctiveness, even if the dilution does not trigger any confusion or adversely compete with trademark owners. Trademark dilution refers to the phenomenon that a trademark, which is similar enough to an existing trademark to confuse customers, is legally used by someone other than the existing trademark owner. As the trademark dilution significantly impairs the trademark's distinctiveness and even results in severe trademark infringement problems in the U.S., the FTDA was enacted for the sake of strengthening the protection against trademark dilution for trademark owners. Specifically, according to FTDA, a trademark owner is not required to provide any evidence of actual trademark infringement but can get an injunction as long as the owner is able to convince a judge of the potential dilution issue. Heath and Mace (2020) indicate that following the passage of FTDA in 1996, the number of trademark related lawsuits substantially escalated[15] , and the costs of entering the related product market drastically increased for potential new entrants. It had become significantly more costly and difficult for the approval of new filed trademarks since FTDA became federal law, as the newly filed trademarks must exhibit their own quality and distinctiveness to avoid litigation under FTDA. Therefore, we argue that FTDA significantly enhances the bar of generating product innovation. Companies need to submit high-quality and distinctive trademark applications for their goods and services to circumvent trademark litigation and get the approval of new trademark applications.

Consequently, trademarks successfully granted after FTDA are presumably more valuable representing product innovation than those before the FTDA. The second natural experiment is based on the decision of the U.S. Supreme Court in 2003 (*Moseley v. V Secret Catalogue, Inc.*), which was ruled in March 2003. *Moseley v. V Secret Catalogue, Inc.* limits the claim of trademark dilution. Specifically, to successfully claim trademark dilution, necessary proof of actual economic damages is required. Therefore, *Moseley v. V Secret Catalogue, Inc.* in 2003 is viewed as a rebuke to the FTDA's too general legal requirements of claiming trademark dilution

(Pulliam, 2003 and Heath and Mace, 2020) in turn, nullifies the effectiveness of FTDA. Indeed, Heath and Mace (2020) find that claims of trademark dilutions at the federal level declined drastically starting from 2003.

If product innovation output indeed reduces the likelihood of becoming IPO targets for newly listed, we should expect the effect is even stronger after the passage of FTDA starting from 1996. Conversely, since the Supreme Court decision in 2003 (*Moseley v. V Secret Catalogue, Inc.*) nullifies the effectiveness of FTDA, we should observe an opposite effect of FTDA. Specifically, the link between the product innovation output and the likelihood of becoming IPO targets should weaken following the Supreme Court decision in 2003. Furthermore, as stated by Heath and Mace (2020), the FTDA and *Moseley v. V Secret Catalogue, Inc.* only apply to famous trademarks, which are considered a subset of firms' all registered trademarks. We, therefore, need to define famous trademarks to perform natural experiments. Although there is no perfect definition for the famousness of trademarks, we follow Heath and Mace (2020) to define famous trademarks as those trademarks that are registered in 1974 or earlier and remain active after the two natural experiments. We perform difference-in-difference (DID) analysis for the two natural experiments. Our DID model is specified as:

$$\begin{aligned} IPO\ targets\binom{1}{0}_{i,t} &= \alpha + \beta_1 \cdot Famous\ trademark_i + \beta_2 \cdot PostFTDA + \beta_3 \cdot PostMosley + \beta_4 \\ &\cdot Famous\ trademark_i \times PostFTDA + \beta_5 \cdot Famous\ trademark_i \times PostMosley \\ &+ Controls + \varphi_k + \varphi_t + \varphi_s + \varepsilon_{i,t} \quad (5) \end{aligned}$$

where $PostFTDA$ is a dummy variable that equals one for the years after 1995 and zero otherwise. We code the year 1996 as one as the law became effective in January. In addition, *PostMosley* is a dummy variable that takes the value of one for the years after 2002 and zero otherwise. We code the year 2003 as one because the court decision is ruled in March (Heath and Mace, 2020). Further, *Famous trademark* is an indicator variable that equals one if an IPO firm has produced famous trademarks prior to going public and zero otherwise. Our interest is the interaction term of $Famous\ trademark_i \times PostFTDA$ and $Famous\ trademark_i \times PostMosley$, we expect the coefficient β_4 to be negative while β_5 to be positive.

Table 7 provides the results of our DID estimation.[16] The results in Column (1) confirm our expectations. Specifically, the coefficient of *Famous trademark* × *PostFTDA* is negative and statistically significant at the 1% level, indicating that stronger trademark protection stemming from FTDA lead to an even stronger negative link between product innovation and the likelihood of getting acquired shortly after the IPO. In addition, the coefficient of *Famous trademark* × *PostMosely* is positive and statistically significant at the 1% level, suggesting that the negative relationship between product innovation and the likelihood of becoming IPO targets attenuated along with the effect of FTDA being nullified by the U.S. Supreme Court decision of *Moseley v. V Secret Catalogue, Inc.* Overall, we interpret these results as support for the negative link between trademarks and the likelihood of becoming IPO targets.

Furthermore, following Mace and Heath (2020), we perform a placebo test using the *Trademark Law Revision Act* (TLRA), which was enacted but revoked shortly after the passage in 1988. Performing such a placebo test intends to further confirm that established product innovation output has a significant impact for IPO firms on the likelihood of getting acquired as IPO targets. Since the TLRA has been revoked and never come into effect, we should not observe any significant impact of the TLRA on the link between product innovation and the likelihood of becoming IPO targets. To perform the placebo test, we further include an interaction term of *Famous trademark* × *PostTLRA* in our DID estimation. *PostTLRA* is a dummy variable that equals one for the years later than 1988, and zero otherwise. Column (2) of Table 8 reports the

[16] To balance our sample to perform the DID analysis and eliminate the possible impact of the *Trademark Law Revision Act* (TLRA) in 1988, we exclude the observations before 1990 for our first DID estimation without the placebo test using TLRA in Column (1) in Table 7.

result of the placebo test. Consistent with our expectation, the coefficient of *Famous trademark × PostTLRA* is not statistically significant, while the empirical results of *Famous trademark × PostFTDA and Famous trademark × PostMosley* remain unchanged. Thus, we conclude that the placebo test further increases the robustness of our main empirical finding.

—Please insert Table 7 about here—

5. Robustness checks

In this section, we conduct several robustness checks.

5.1. Product innovation after IPO

Thus far, our empirical analyses strongly support our hypotheses that IPOs with newly developed product innovation prior to an IPO are less likely to become acquisition targets, even after addressing issues related to potential selection bias and endogeneity. However, to eliminate the possibility that other omitted factors could drive the negative relation between product innovation and the likelihood of becoming M&A targets, we perform a series of robustness checks in this section.

We first confirm whether our results change by considering trademarks granted after going public. IPO firms could generate new trademarks in each fiscal year within three years after the IPO. Therefore, we replace our measure for product innovation by including the trademarks generated within three years after the public listing stage and perform a similar logit regression analysis as our baseline model. The results are displayed in Table 8 and suggest that including trademarks after IPO does not alter our baseline conclusion.

5.2. Excluding the 1999–2000 bubble period

Next, to ensure that our results are not driven by IPOs that went public during the 1999-2000 bubble period, we re-estimate all regressions by excluding observations in this period. We again confirm that our results in all empirical settings remain qualitatively similar.

5.3. Controlling for institutional blockholders

De and Jindra (2012) find a significant relationship between post-IPO institutional ownership and the likelihood that firms will become acquisition targets. Therefore, we control for the percentage of institutional blockholders in all estimations, and our results remain qualitatively unchanged.

5.4. Controlling for anti-takeover provisions

Takeover defenses can insulate firm management from short-term pressure in the stock market and ensure that managers focus on innovative projects that generate long-term value. Chemmanur and Tian (2018) find indeed that firm-level anti-takeover provisions can increase firms' patenting activities. Field and Karpoff (2002) indicate that many firms have already adopted anti-takeover provisions by the time they go public. Therefore, we examine whether the lower likelihood that innovative IPOs will be acquired is driven by anti-takeover provisions adopted when they go public. To do so, we manually collect anti-takeover provisions from the IPO prospectus. We focus on the five anti-takeover provisions (Chemmanur, Paeglis, and Simonyan, 2011): staggered boards, poison pills, a supermajority required to approve mergers, a supermajority required to amend the charter or bylaws, and unequal voting rights. We then create an anti-takeover index (ranging from 0 to 5) by adding each anti-takeover provision's dummy value. Results in Table 8 confirm that adopting anti-takeover provisions indeed significantly decreases IPO firms' likelihood to be taken over. However, after controlling for anti-takeover provisions, IPOs with product innovation are consistently less likely to become IPO targets.

5.5. Excluding the firms with zero pre-IPO trademarks

Furthermore, we examine whether the negative relation between product innovation and the likelihood of getting acquired is driven by firms that have never engaged in product innovation prior to the IPO. We exclude all observations with zero product innovation at the pre-IPO stage. The results shown in Table 8 indicate that the negative relation between IPOs' newly launched product innovation prior to going public and the likelihood of becoming IPO targets is not driven by firms with zero patents.

—Please insert Table 8 about here—

6. Further analysis

In this Section, we discuss various channels through which trademarks affect the likelihood of becoming IPO targets.

6.1. Product market competition channel

Our rationale for the relationship between IPOs' newly developed product innovation and the likelihood of becoming IPO targets is based on the product market competition perspective. Gu (2016) develops a theoretical framework of standard real options to test the joint effect of innovation engagement and product market competition. The model postulates that unique products are more valuable in competitive industries than in concentrated industries. Therefore, if product innovation signifies the viability against fierce product market competition, we expect that IPOs with newly launched product innovation in highly competitive industries are more capable of growing organically than those in concentrated industries.

To empirically test this channel, we include an interaction term between product innovation and product market competitiveness. Specifically, we interact our baseline measure of product innovation (trademark counts) with the Herfindahl-Hirschman Index (HHI). HHI is a proxy for product market competition. Specifically, HHI is computed as the sum of the squared market shares of each firm's total sales in a 3-digit standard industrial classification (SIC) industry (Gu, 2016; Hoberg and Phillips, 2016). A higher HHI indicates a less competitive industry (more concentrated market), whereas a lower HHI implies a more competitive industry. The market share of a single company is calculated using the firm's net sales, which are retrieved from Compustat and scaled by the total sales of a specific industry. If the negative relation between product innovation and the likelihood of becoming IPO targets is more pronounced in highly competitive industries, we can expect to observe a positive coefficient for the interaction term.

Table 9 presents the results. We find that coefficients for the interaction terms in both the full sample and the post-PSM sample are positive and statistically significant at conventional levels, confirming the product market competition channel. We also interact other trademark proxies with HHI, and the results are qualitatively similar. Therefore, as trademarks are more valuable in highly competitive industries, IPOs with established trademarks are more confident in the value of their growth as independent firms.

—Please insert Table 9 about here—

6.2. Long-term value creation channel

We argue that IPOs with more established product innovation prefer to grow organically as independent firms, as such firms commit to long-term growth driven by product innovation. Thus, these firms have confidence in the long-term value created by innovation and are dedicated to maintaining their innovativeness in product market. To empirically validate our assumption, we investigate long-term firm performance in two regards. First, we examine the long-term stock and financial performance within the three years directly following the IPO. Second, we examine the firms' innovation performance within three years of the IPO anniversary. We measure long-term stock performance using the three years' post-IPO market-adjusted buy-and-hold returns (*BHAR*) since IPO. *BHAR* is calculated by the buy-and-hold return of an IPO firm less the buy-and-hold return of the CRSP equal-weighted index starting from the month after the IPO month to the relevant fiscal year-end. Additionally, we measure long-term financial performance by *ROA*.

The results in Column (1), Table 10 reveal that trademarks significantly boost the post-IPO long-term stock performance for independent IPOs. Similarly, in Column (2), *ROA* during the post-IPO period is positively connected to IPOs' established product innovation. The positively significant coefficient of the aggregate number of trademarks implies that a one-standard-deviation increase of trademark count leads to a 6.5% increase in stock performance as well as a 6.9% rise in financial performance. Column (3) and (4), Table 10 exhibit the post-IPO product and technological innovation performance for independent IPOs. Post-IPO product innovation is measured based on the cumulative number of successfully registered trademarks during the three years directly following the IPO milestone, whilst technological innovation is proxied with the cumulative number of successfully granted patents within the three years post-IPO. We find that product innovation is a long-term commitment, and independent IPOs with more trademarks prior to going public tend to maintain their innovativeness in the product market. Trademarks successfully registered and patents granted within three years after going public are positively associated with pre-IPO product innovation. One-standard-deviation increase in pre-IPO trademark count leads to a 51.01% increase in post-IPO trademark registrations and 9.3% increase in post-IPO granted patents within three years post-IPO. We, therefore, confirm that increased financial and innovation performance supports the channel of long-term value creation.[17]

—Please insert Table 10 about here—

6.3. M&A deal initiation channel

Thus far, we have demonstrated that newly developed product innovation is significantly associated with the likelihood of becoming IPO targets. However, we still need to examine whether M&A deals are driven by the supply or demand side. In other words, are M&A deals initiated by targets themselves or corporate raiders. Masulis and Simsir (2018) investigate why several acquisition targets intentionally seek potential bidders to initiate an acquisition. They find that target-initiated deals tend to be financially weak and are more likely to happen during the negative industry and economic shocks.

Nevertheless, financially weak firms might be meanwhile less competitive in their respective product markets. Therefore, it could be the case that IPO firms lacking viability in the product market (trademarks) are prone to seek a buyer to support their market competition voluntarily. Thus, for IPO targets with fewer trademarks (less competitive against product market competition), such deals are supposed to be driven by the M&A supply side, while for IPO targets with more trademarks (more viable against product market contest), such deals tend to be driven by the M&A demand side. To empirically investigate this channel, we perform a logit regression for the subsample of IPO targets. The dependent variable of the logit model is a binary variable that equals one if the merger is initiated by the IPO target itself, and zero if the deal is initiated by the bidder. Product innovation is measured by the above-mentioned six trademark proxies.

As indicated by Masulis and Simsir (2018) and Fidrmuc and Xia (2017), the only reliable

[17] In unreported tests, we use other trademark proxies to examine IPOs' long-term performance. The results largely remain qualitatively similar.

measure of M&A deal initiation thus far consists of reading the electronic filings, available in the SEC's EDGAR database, that contains information on the entity initiating a merger include DEFM14A, PREM14A, SC14D9, and S-4 filings. Among these, one section reports "the background of the merger." From this section, we can learn which party initiates contact to propose an M&A deal by reading the details provided therein. If a deal is initiated by a target, it is typically described using wording such as "*the firm management considers various strategic alternatives that include a possible sale of the company*," as well as "*the management hires an investment bank to evaluate strategic alternatives*." Conversely, suppose a bidder initiates a deal. In this case, we find wording describing a scenario in which a potential corporate raider initially approaches the target firm's management and proposes a merger deal, such as that in which a buyer "expresses an interest in exploring a strategic combination." The section regarding "The background of the merger" indicates that after the proposal, the board considers the possibility and then informs the buyer of its decision after the discussion. Typically, two scenarios then unfold. First, the target management actively negotiates with the buyer and agrees to the deal after multiple rounds of negotiations. Second, the target may then contact "white knights" to invigorate the competition and thereby sell the firm for a better price. We classify such deals as bidder-initiated, regardless of whether the deal is completed by the first potential buyer or another bidder. It is worth noting that the electronic files of public firms in EDGAR are not available until 1996. Thus, to test this channel, we use our sub-sample between 1996 and 2013. It includes 234 of the 271 IPO targets based on data availability. Among the 234 M&A deals, 123 are target-initiated, while 111 are bidder-initiated. Appendix B illustrates two specific examples of target and bidder-initiated M&A deals.

Table 11 indicates the empirical results of the link between newly launched product innovation and M&A deal initiation of IPO targets. The results exhibit partial support for the M&A deal initiation channel. Among the six proxies for product innovation, we can see that IPOs with diversified trademarks as well as exploitation trademarks are less likely to initiate M&A deals. In other words, M&A deals involving IPO firms with more product innovation are more likely to be initiated by the corporate raiders. In sum, we find that IPO firms with a higher level of developed product innovation are more capable of growing organically to fend themselves against product market competition and therefore are less likely to ask their investment banks to contact potential buyers initiatively. However, they may accept the M&A deals initiated by potential bidders if they believe the offer price is sufficiently high.

—Please insert Table 11 about here—

6.4. Takeover costs channel

Based on our analysis of M&A deal initiation channel, we observe that IPO M&A deals involving more product innovation are less likely to be driven by the supply side (target-initiated deals). In other words, the subjective will of IPOs with higher capability of fending themselves against product market race is more likely aimed at growing as independent firms to realize their long-term value. Hence, these IPO firms do not intentionally initiate a merger. However, as we mentioned previously if IPOs with more trademarks ultimately agree to a trade sale, they must be compensated with a sufficient premium. Put it differently, it should be quite costly for corporate raiders to buy IPO targets with more trademarks. The purpose of this section is to empirically examine the impact of product innovation on takeover costs. We expect that trademarks substantially increases the takeover costs for buyers.

We measure the takeover costs using the takeover premium, following Moeller et al. (2004 and 2005), Officer (2007), Li (2013), and Masulis and Simisir (2018). Specifically, the measure is a value-based one of the takeover premia, which equals the difference between the deal and market values of the acquisition target and is then scaled by the market value of the acquisition target. Schwert (1996, 2000) indicates that the acquisition targets' cumulative abnormal returns begin increasing around 42 days before the merger is announced. Therefore, we use the market value of the M&A target 50 days before the announcement of the M&A itself (Wu and Chung, 2019). To analyze takeover costs, we further include M&A specific variables: the percentage of cash payment (*Cash*), whether multiple potential acquirers bid on a deal (*Competing*), whether the deal is classified as diversifying (*Diversifying*), and whether the acquirer is a private company (*Go private*).

Table 12 presents our results for takeover costs. We find that product innovation significantly increases the takeover costs for acquirers to buy such IPO targets, regardless of which proxy is used for measuring product innovation. For example, the positive and significant coefficient of *Ln (1+Trademarks)* implies that an increase of one in the standard deviation of trademark count is linked to a 14% increase in the takeover premium, which is equivalent to a $141.87 thousand increase in the aggregate dollar amount. We interpret this finding as an indicator of further support for our argument. IPOs with more newly developed trademarks are more capable of growing as independent firms. However, to entice such IPOs to relinquish their initial plan to grow independently, acquirers must pay a sufficiently high price to compensate the target. The value increase in the aggregate dollar amount implies that acquiring IPOs with more trademarks is substantially costly.

—Please insert Table 12 about here—

7. Conclusion

Why IPO firms become acquisition targets? Unlike previous studies, we primarily focus on IPO firms' established product innovation prior to public offerings, consider their already developed product innovation outout as the proxy of product market competitiveness, and investigate the causal relationship between IPO firms' successfully granted trademarks and the likelihood of becoming IPO targets.

Our empirical analyses show that less innovative IPOs in product market are more likely to become M&A targets shortly after their public listing. Conversely, more innovative IPOs in product market are more likely to grow organically as independent firms. Our results remain robust after addressing a potential selection bias using a propensity score matching routine, as well as dealing with the endogeneity concern by applying IV analysis and designing a quasi-natural experiment as an exogenous shock.

Furthermore, we show that the negative relationship between the quantity of successfully granted trademarks and the likelihood of becoming IPO targets stems from the product market competition perspective. Specifically, the negative relation is more pronounced in highly competitive industries. Thus, IPOs with more developed trademarks are more capable of fend themselves against the ferocious product market race in highly competitive industries and therefore are more likely to grow independently. Moreover, the choice of growing independently is justified by better post-IPO performance. Our long-term value creation channel suggests that IPOs with more product innovation have better post-IPO financial performance and better post-IPO innovation performance in the product market than IPOs with less product innovation.

To better understand whether a higher probability of becoming IPO targets for entrepreneurial firms that are less competitive in product market, we examine the potential channels from the IPO targets side to check the M&A deal initiator. We find that firms that are less capable of competing against the product market contest are more likely to be the deal initiator than firms that are more viable against product market race. Additionally, the financial cost of a merger is significantly higher for M&A bidders to acquire more innovative IPOs in product market. Thus, the negative relationship between product innovation and the likelihood of becoming an IPO target is driven by the M&A supply side.

Therefore, we conclude that product market competitiveness significantly affects the post-IPO growth pathways for newly listed startups. IPOs with superior product market competing positions prefer to grow independently, while IPOs with inferior competing positions on product market favor integrating with established firms via acquisitions to support their product market competitiveness.

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Table 1: Sample overview

Table 1 represents the annual and industrial distribution for all the IPOs in our sample between 1980 and 2013. Panel A reports the annual number of IPOs, along with IPOs becoming IPO targets shortly after going public, together with distributional percentages of IPO targets. The annual amount of gross proceeds raised through going public and the total M&A deal value of IPO targets are also reported. Panel B reports the annual number and deal value of M&As for IPO targets and those including IPOs eventually becoming M&A targets as seasoned firms (our cut-off is the tenth fiscal year following IPO), together with distributional percentages of the number of the transaction value of IPO targets. Panel C reports the industry classification of IPO firms (including the firms becoming IPO targets) in our sample according to the 49 Fama-French industry classifications, together with distributional percentages of industries.

Panel A: IPOs and IPO targets

Year	IPOs	IPO targets	Percentage	IPO proceeds ($millions)	M&A deal value ($millions)
1980	45	2	4.44%	99.03	254.42
1981	97	3	3.09%	220.90	138.58
1982	46	0	0.00%	104.86	0.00
1983	245	14	5.71%	682.50	2,169.24
1984	102	5	4.90%	236.80	795.93
1985	108	11	10.19%	296.06	1,505.16
1986	249	23	9.24%	688.86	2,151.31
1987	183	20	10.93%	540.74	2,339.13
1988	69	6	8.70%	217.11	692.19
1989	52	0	0.00%	172.29	0.00
1990	67	2	2.99%	220.47	274.70
1991	195	13	6.67%	659.20	1,683.47
1992	248	17	6.85%	853.30	6,888.29
1993	356	37	10.39%	1,218.16	13,466.24
1994	289	39	13.49%	941.00	13,747.34
1995	327	58	17.74%	1,181.24	25,614.13
1996	270	27	10.00%	938.62	23,079.91
1997	250	37	14.80%	880.61	42,888.30
1998	143	21	14.69%	528.98	16,483.97
1999	312	66	21.15%	1,254.04	43,508.77
2000	253	42	16.60%	1,050.30	15,490.90
2001	36	5	13.89%	144.61	5,794.24
2002	35	6	17.14%	149.68	3,746.17
2003	28	3	10.71%	118.92	3,135.51
2004	88	12	13.64%	365.43	9,823.23
2005	67	7	10.45%	277.35	1,424.10
2006	81	10	12.35%	347.32	4,144.36
2007	96	9	9.38%	430.02	8,649.63
2008	12	2	16.67%	56.58	2,097.48
2009	14	0	0.00%	72.48	0.00
2010	48	3	6.25%	215.96	1,614.37
2011	52	5	9.62%	246.50	8,350.30
2012	46	9	19.57%	205.00	11,521.79
2013	87	7	8.05%	377.48	12,862.74
Total	**4,596**	**521**	**11.34%**	**15,992.40**	**286,335.90**

Panel B: Distribution of IPO targets in the M&A market by year

Year	IPO Targets	M&A targets	Percentage (number)	Deal value of IPO targets ($millions)	Deal value of M&A targets ($millions)	Percentage (value)
1980	2	11	18.18%	254.42	3,966.51	6.41%
1981	3	17	17.65%	138.58	2,061.32	6.72%
1982	0	9	0.00%	0.00	795.93	0.00%
1983	14	55	25.45%	2,169.24	8,833.75	24.56%
1984	5	20	25.00%	795.93	2,055.61	38.72%
1985	11	24	45.83%	1,505.16	2,755.14	54.63%
1986	23	33	69.70%	2,151.31	7,410.85	29.03%
1987	20	22	90.91%	2,339.13	2,354.71	99.34%
1988	6	7	85.71%	692.19	1,104.51	62.67%
1989	0	0	0.00%	0.00	0.00	0.00%
1990	2	2	100.00%	274.70	274.7	100.00%
1991	13	13	100.00%	1,683.47	1,683.47	100.00%
1992	17	18	94.44%	6,888.29	7,071.8	97.41%
1993	37	38	97.37%	13,466.24	14,590.49	92.29%
1994	39	40	97.50%	13,747.34	13,975.12	98.37%
1995	58	58	100.00%	25,614.13	25,614.13	100.00%
1996	27	51	52.94%	23,079.91	48,737.96	47.36%
1997	37	63	58.73%	42,888.30	57,201.27	74.98%
1998	21	40	52.50%	16,483.97	23,972.69	68.76%
1999	66	110	60.00%	43,508.77	60,935.65	71.40%
2000	42	85	49.41%	15,490.90	46,251.36	33.49%
2001	5	11	45.45%	5,794.24	10,083.8	57.46%
2002	6	11	54.55%	3,746.17	10,001.4	37.46%
2003	3	8	37.50%	3,135.51	7,310.19	42.89%
2004	12	26	46.15%	9,823.23	28,496.48	34.47%
2005	7	22	31.82%	1,424.10	26,479.63	5.38%
2006	10	21	47.62%	4,144.36	12,148.54	34.11%
2007	9	30	30.00%	8,649.63	53,011.36	16.32%
2008	2	3	66.67%	2,097.48	3,581.06	58.57%
2009	0	2	0.00%	0.00	2,832.82	0.00%
2010	3	9	33.33%	1,614.37	13,521.97	11.94%
Total	**500**	**859**	**58.21%**	**253,601.07**	**499,114.22**	**50.81%**

Panel C: Industry classification

Fama-French Industry	IPOs	Percentage	IPO targets	Percentage
Agriculture	14	0.30%	2	0.38%
Aircraft	11	0.24%	0	0.00%
Apparel	57	1.24%	1	0.19%
Automobiles and trucks	49	1.07%	4	0.77%
Beer and Liquor	11	0.24%	2	0.38%
Business services	429	9.33%	63	12.09%
Business supplies	36	0.78%	4	0.77%
Candy and soda	13	0.28%	3	0.58%
Chemicals	57	1.24%	5	0.96%
Coal	10	0.22%	0	0.00%
Communication	185	4.03%	23	4.41%
Computer hardware	177	3.85%	15	2.88%
Computer software	703	15.30%	126	24.18%
Construction	46	1.00%	2	0.38%
Construction materials	52	1.13%	9	1.73%
Consumer goods	69	1.50%	7	1.34%
Defense	5	0.11%	2	0.38%
Electrical equipment	43	0.94%	3	0.58%
Electronic equipment	377	8.20%	36	6.91%
Entertainment	66	1.44%	7	1.34%
Fabricated products	9	0.20%	1	0.19%
Food products	36	0.78%	4	0.77%
Healthcare	149	3.24%	17	3.26%
Machinery	92	2.00%	6	1.15%
Measuring equipment	90	1.96%	8	1.54%
Medical equipment	214	4.66%	33	6.33%
Mining	6	0.13%	0	0.00%
Others	45	0.98%	0	0.00%
Personal services	59	1.28%	7	1.34%
Petroleum and natural gas	138	3.00%	13	2.50%
Pharmaceutical products	380	8.27%	23	4.41%
Precious metals	9	0.20%	0	0.00%
Printing and publishing	28	0.61%	0	0.00%
Recreation	49	1.07%	3	0.58%
Restaurants and hotels	107	2.33%	13	2.50%
Retail	302	6.57%	31	5.95%
Rubber and plastic products	26	0.57%	1	0.19%
Shipbuilding equipment	11	0.24%	0	0.00%
Shipping containers	11	0.24%	2	0.38%
Steel works	55	1.20%	4	0.77%
Textiles	20	0.44%	2	0.38%
Tobacco products	5	0.11%	0	0.00%
Transportation	130	2.83%	10	1.92%
Utilities	47	1.02%	5	0.96%
Wholesale	168	3.66%	24	4.61%
Total	**4,596**	**100.00%**	**521**	**100.00%**

Table 2: Summary statistics for IPOs

This table reports summary statistics (mean, median, and the number of observations) for all variables of independent IPOs and IPO targets between 1980 and 2013. All variable definitions are described in Table A1. We report the pairwise differences in means (*t*-test) and medians (Wilcoxon test) of the variables between independent and IPO targets. Related *p*-values are shown to the right in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	***Independent IPOs* (N=4,075)**		***IPO Targets* (N=521)**					
	Mean	Median	Mean	Median	Differences in means		Differences in medians	
Ln (1+Trademark)	1.056	0.693	0.820	0.693	0.236	(0.363)	0.000	(0.706)
Ln (1+Diversity)	0.629	0.693	0.568	0.693	0.061	(0.105)	0.000	(0.111)
Ln (1+Exploitation)	0.522	0.693	0.481	0.000	0.041	(0.982)	0.693	(0.831)
Ln (1+Exploration)	0.839	0.000	0.553	0.000	0.286	(0.112)	0.000	(0.146)
Ln (1+Marketing)	0.206	0.000	0.138	0.000	0.068	(0.192)	0.000	(0.316)
Ln (1+Product)	1.012	0.693	0.782	0.693	0.230	(0.385)	0.000	(0.696)
Advertise	0.556	0.000	0.123	0.000	0.433*	(0.067)	0.000***	(0.007)
Age	16.238	9.000	9.425	6.000	6.813**	(0.036)	3.000*	(0.065)
BHAR	-0.135	-0.568	-0.050	-0.479	-0.085	(0.238)	-0.089***	(0.000)
Cash ratio	0.247	0.163	0.357	0.316	-0.110***	(0.000)	-0.153***	(0.000)
HHI	742.750	519.651	506.709	410.598	236.041*	(0.056)	109.053*	(0.060)
IPO proceeds	3.628	3.651	4.007	4.093	-0.379***	(0.000)	-0.442***	(0.000)
KZ index	-352.556	-33.787	-168.414	-59.543	-184.142	(0.213)	25.756	(0.323)
Leverage	0.184	0.043	0.099	0.006	0.085***	(0.002)	0.037***	(0.000)
Liquidity	0.661	0.718	0.744	0.825	-0.083***	(0.000)	-0.107***	(0.000)
Ln (1+Patent)	0.182	0.000	0.165	0.000	0.017	(0.534)	0.000	(0.968)
M&A activity	0.004	0.001	0.005	0.002	-0.001**	(0.013)	-0.001***	(0.000)
R&D	0.207	0.022	0.120	0.065	0.087*	(0.064)	-0.043***	(0.002)
ROA	0.038	0.100	-0.107	-0.059	0.145***	(0.002)	0.159***	(0.001)
Sales growth	3.329	0.335	2.219	0.712	1.110	(0.515)	-0.377***	(0.002)
Size	560.000	133.075	576.388	290.784	-16.388	(0.541)	-157.709***	(0.000)
Tobin's q	3.523	1.930	5.008	2.580	-1.485**	(0.017)	-0.650***	(0.002)
Underwriter	7.435	8.001	8.056	9.001	-0.621***	(0.000)	-1.000***	(0.000)
VC	0.486	0.000	0.790	1.000	-0.304***	(0.000)	-1.000***	(0.000)

Table 3: The influence of pre-IPO product innovation and the likelihood of becoming IPO targets

This table reports the results of logit regression analysis (Panel A is a cross-sectional analysis, whilst Panel B represents panel analysis) for independent IPOs and IPO targets between 1980 and 2013. The dependent variable is a dummy variable that equals 1 if the IPO firm gets acquired within the three years after going public, and 0 otherwise. Column (1) to Column (6) report the results using six product innovation measures: *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*. See Table A1 for detailed definition. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at two-digit SIC industry level. *Industry, Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademark)	-0.475***					
	(0.001)					
Ln (1+Diversity)		-0.476**				
		(0.041)				
Ln (1+Exploitation)			-0.116			
			(0.605)			
Ln (1+Exploration)				-0.603***		
				(0.000)		
Ln (1+Marketing)					-0.315	
					(0.384)	
Ln (1+Product)						-0.553***
						(0.001)
Advertise	-0.003	0.000	-0.007	0.004	-0.011	0.007
	(0.920)	(0.993)	(0.852)	(0.917)	(0.683)	(0.862)
Age	-0.022**	-0.031**	-0.031**	-0.028**	-0.017*	-0.031**
	(0.050)	(0.020)	(0.027)	(0.014)	(0.067)	(0.015)
BHAR	0.184***	0.199***	0.193***	0.201***	0.152***	0.213***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Cash ratio	-0.897*	-0.865	-0.823	-0.955	-0.652	-0.960*
	(0.088)	(0.113)	(0.124)	(0.105)	(0.174)	(0.096)
HHI	-0.001**	-0.001*	-0.001	-0.001**	-0.001*	-0.001*
	(0.047)	(0.094)	(0.137)	(0.031)	(0.090)	(0.073)
IPO proceeds	0.725**	0.924***	0.902***	0.808***	0.543**	0.944***
	(0.013)	(0.007)	(0.007)	(0.008)	(0.040)	(0.007)
KZ index	0.000	0.000	0.000	0.000	0.000	0.000

	(0.417)	(0.408)	(0.449)	(0.227)	(0.696)	(0.295)
Leverage	-1.210	-1.387	-1.323	-1.542	-0.690	-1.588
	(0.458)	(0.492)	(0.502)	(0.411)	(0.613)	(0.453)
Liquidity	2.512***	2.638***	2.640***	2.562***	2.200***	2.753***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln (1+Patent)	-0.557***	-0.669***	-0.674***	-0.584***	-0.522***	-0.645***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.006)	(0.000)
M&A activity	11.596	27.367	26.814	18.105	4.185	24.008
	(0.653)	(0.449)	(0.457)	(0.510)	(0.841)	(0.507)
R&D	-0.395	-0.654	-0.731	-0.341	-0.439	-0.528
	(0.451)	(0.401)	(0.347)	(0.589)	(0.259)	(0.506)
ROA	-1.381**	-1.762***	-1.838***	-1.476**	-1.285**	-1.578**
	(0.018)	(0.007)	(0.004)	(0.025)	(0.015)	(0.025)
Sales growth	-0.020	-0.032*	-0.028	-0.025*	-0.010	-0.037*
	(0.137)	(0.094)	(0.113)	(0.080)	(0.228)	(0.072)
Size	-0.000*	-0.000**	-0.000**	-0.000*	-0.000	-0.000*
	(0.088)	(0.041)	(0.031)	(0.077)	(0.226)	(0.076)
Tobin's q	-0.056*	-0.053	-0.052	-0.061*	-0.050	-0.057
	(0.070)	(0.114)	(0.116)	(0.057)	(0.156)	(0.111)
Underwriter	0.248*	0.303**	0.304**	0.324**	0.187	0.310**
	(0.056)	(0.025)	(0.023)	(0.015)	(0.239)	(0.020)
VC	0.664	0.677	0.622	0.701	0.556	0.754
	(0.297)	(0.350)	(0.391)	(0.298)	(0.295)	(0.295)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,952	1,952	1,952	1,952	1,952	1,952
Pseudo R^2	0.635	0.652	0.650	0.625	0.606	0.658

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademark)	-0.619***					
	(0.000)					
Ln (1+Diversity)		-0.694***				
		(0.001)				
Ln (1+Exploitation)			-0.355			
			(0.141)			
Ln (1+Exploration)				-0.723***		
				(0.000)		
Ln (1+Marketing)					-0.559	
					(0.198)	
Ln (1+Product)						-0.673***
						(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,472	7,472	7,472	7,472	7,472	7,472
Pseudo R^2	0.594	0.501	0.497	0.506	0.498	0.581

Table 4: Survival analysis for the effect of pre-IPO product innovation on the speed of becoming IPO targets

This table reports the results of the survival analysis using Cox Hazard Model for IPOs between 1980 and 2013 using the post-matching sample to examine the speed of IPOs becoming acquisition targets. The dependent variable represents the duration that an IPO stays on the stock exchange. For IPOs becoming acquisition targets, the duration is measured with the days between the issue date and the date of acquisition announcement. For independent IPOs, the duration is measured with the days between the issue date and the last day of the third fiscal year. Column (1) to Column (6) report the results of the cross-sectional Cox Hazard model using six product innovation measures: *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*. See Table A1 for a detailed definition. We report ***Hazard Ratios*** in parentheses below. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademark)	-0.009**					
	(0.991)					
Ln (1+Diversity)		-0.014**				
		(0.986)				
Ln (1+Exploitation)			-0.005			
			(0.995)			
Ln (1+Exploration)				-0.006*		
				(0.994)		
Ln (1+Marketing)					-0.007	
					(0.993)	
Ln (1+Product)						-0.009***
						(0.991)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,952	1,952	1,952	1,952	1,952	1,952

Table 5: Pre-IPO product innovation and the likelihood of becoming IPO targets (post PSM)

This table reports the results of a post-matching logit regression analysis for IPOs targets and predicted IPO targets between 1980 and 2013. Predicted IPO targets are selected from the independent IPOs as those with the propensity scores closest to those of each actual IPO target. The dependent variable is a dummy variable that equals 1 if the IPO firm gets acquired within the three years after going public and 0 otherwise. Column (1) to Column (4) report the results of the regression using six different measures of product innovation: *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*. See Table A1 for a detailed definition. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at two-digit SIC industry level. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademark)	-1.405***					
	(0.000)					
Ln (1+Diversity)		-1.557***				
		(0.000)				
Ln (1+Exploitation)			-1.341***			
			(0.000)			
Ln (1+Exploration)				-1.545***		
				(0.000)		
Ln (1+Marketing)					-0.299	
					(0.729)	
Ln (1+Product)						-1.505***
						(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	260	260	260	260	260	260
Pseudo R^2	0.516	0.482	0.467	0.523	0.444	0.520

Table 6: Instrumental variable (IV) analysis

This table reports the second-stage results of the two-stage instrumental variable regression analysis (IV probit) addressing the potential endogeneity issue of trademarks. The first-stage results are reported in Table A3 in the Appendix The IV in the first stage estimation is *Examiner leniency*, which is the trademark examiner's leniency averaged over all trademark applications submitted by an IPO firm. We take the predicted value of six trademark-related measures from the first stage regression analysis and include it in the second-stage estimation. The results of the second-stage estimation are reported in Column (1)-(6) using six product innovation proxies, respectively. In the second-stage analysis, the dependent variable is a dummy variable that equals 1 if the IPO firm gets acquired within the three years after going public, and 0 otherwise. The explanatory variables are the predicted value of the six proxies of product innovation. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at two-digit SIC industry level. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademarks) $_{predicted}$	-0.879***					
	(0.000)					
Ln (1+Diversity) $_{predicted}$		-1.437***				
		(0.000)				
Ln (1+Exploitation) $_{predicted}$			-1.446***			
			(0.000)			
Ln (1+Exploration) $_{predicted}$				-1.024***		
				(0.000)		
Ln (1+Marketing) $_{predicted}$					-2.821***	
					(0.000)	
Ln (1+Product) $_{predicted}$						-0.900***
						(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	632	632	632	632	632	632
Stock-Yogo Test	41.520	38.526	24.089	24.007	1.392	49.123
Durbin-Wu-Hausman Test	0.017	0.008	0.005	0.025	0.014	0.019

Table 7: Difference in Differences Analysis

This table reports the results of the difference in differences (DID) analysis of the effect of the *1996 Federal Trademark Dilution Act* (FTDA) as well as the impact of the decision of U.S. Supreme Court in 2003 (*Moseley v. V Secret Catalogue, Inc.*) on the link between product innovation and IPOs' likelihood of becoming acquisition targets. The dependent variable is an indicator variable that equals 1 if the IPO firm gets acquired within the three years after going public, and 0 otherwise. The treatment variable is *Famous trademark*, which equals 1 for the IPO firms with famous trademarks prior to their public offerings, and 0 otherwise. In Column (1), the variables of interest are the interaction term between *PostFTDA* and *Famous trademark* as well as the interaction term between *PostMosley* and *Famous trademark*. *PostFTDA* is a dummy variable that equals 1 for the years later than 1995, and 0 otherwise, whilst *PostMosley* is a dummy variable that equals 1 for the years later than 2002, and 0 otherwise. In Column (2), we further perform a placebo test using the *Trademark Law Revision Act* (TLRA) which was enacted but revoked shortly after the passage in 1988. The variable of interest is the interaction term between *PostTLRA* and *Famous trademark*. *PostTLRA* is a dummy variable that equals 1 for the years later than 1988, and 0 otherwise. Variable definitions are provided in Table A1. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at two-digit SIC industry level. *Industry*, *Year* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Famous trademark	-0.895	0.296
	(0.285)	(0.786)
PostFTDA	1.533***	1.495***
	(0.000)	(0.000)
Famous trademark × PostFTDA	-16.129***	-15.870***
	(0.000)	(0.000)
PostMosley	-0.472	-0.620**
	(0.103)	(0.024)
Famous trademark × PostMosley	0.962***	1.218***
	(0.000)	(0.000)
PostTLRA		0.178
		(0.745)
Famous trademark × PostTLRA		-1.371
		(0.267)
Controls	Yes	Yes
Industry fixed effect	Yes	Yes
State fixed effect	Yes	Yes
Observations	1,585	1,952
Pseudo R^2	0.257	0.254

Table 8: Robustness checks

This table presents the results for several robustness checks for the effect of product innovation on the likelihood of becoming IPO targets. For brevity, we only report the estimates for our key independent variables measuring product innovation: *Ln (1+Trademark)*, as well as for additional control variables. The dependent variable is a dummy variable that equals 1 if the IPO firm gets acquired within the three years after going public, and 0 otherwise. See Table A1 for all variable definitions. Coefficient estimates with *p*-values in parentheses are reported below. *p*-values are calculated using clustered standard errors at two-digit SIC industry level. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)
	Ln (1+Trademark)
(1) Including granted trademarks within the three years after IPO	-1.012***
	(0.000)
(2) Excluding 1999-2000 bubble period	-1.405***
	(0.000)
(3) Controlling for institutional blockholders	-1.488***
	(0.000)
Institutional blockholders	-1.267***
	(0.000)
(4) Controlling for anti-takeover provisions	-0.781***
	(0.000)
Anti-takeover	-4.210***
	(0.001)
(5) Excluding the firms that have zero pre-IPO product innovation	-4.428***
	(0.002)

Table 9: Testing the product market competition channel

This table reports logit regression results for the channel that affects the link between product innovation and the likelihood of becoming acquisition targets for IPO firms: product market competition. The dependent variable is a dummy variable that equals 1 if the IPO firm gets acquired within the three years after going public and 0 otherwise. Column (1) displays the results using the entire sample, whilst Column (2) shows the results using the post-PSM sample. To test the channel, we include an interaction term: *Ln (1+Trademark)* $\times$ *HHI*. See Table A1 for a detailed definition. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at the two-digit SIC industry level. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) **Full sample**	(2) **PSM**
Ln (1+Trademark)	-0.799***	-5.599***
	(0.000)	(0.000)
HHI	-0.001**	-0.018***
	(0.018)	(0.008)
Ln (1+Trademark) $\times$ *HHI*	0.001***	0.011***
	(0.004)	(0.000)
Controls	Yes	Yes
Industry fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
State fixed effect	Yes	Yes
Observations	1,952	260
Pseudo R^2	0.608	0.580

Table 10: Testing the long-term value creation channel

This table reports the regression results for the long-term performance (stock performance, financial performance, and innovation performance) within the three years after going public for independent IPOs. In Column 1, we measure the long-term stock performance by the three years' post-IPO market-adjusted buy-and-hold returns (*BHAR*) since IPO. In Column 2, we measure the long-term financial performance by ROA. In Column 3, we measure the product innovation performance by the natural logarithm of new trademark counts within three years after IPO. In Column 4, we measure the technological innovation performance by the natural logarithm of new patent counts within three years after IPO. See Table A1 for detailed variable definition. We perform the OLS regression analysis to test the long-term value creation channel. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at two-digit SIC industry level. *Industry*, *Year* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	BHAR	***ROA***	***Ln (1+Trademark)$_{post3ys}$***	***Ln (1+Patent)$_{post3ys}$***
Ln (1+Trademark)	0.088*	0.015**	0.488***	0.098***
	(0.053)	(0.012)	(0.000)	(0.001)
Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes
Observations	1,777	1,832	1,839	1,839
R^2	0.336	0.563	0.574	0.685

Table 11: Testing the M&A deal initiation channel

This table reports the results of logit regression analysis for M&A deal initiation of IPO firms between 1996 and 2013. The dependent variable is a dummy variable that equals 1 if an M&A deal is initiated by the target and 0 if a deal is initiated by the bidder. Column (1) to Column (6) report the results using six product innovation measures: *Ln(1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*. See Table A1 for details of variable definition. We report coefficient estimates with *p*-values in parentheses below. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at two-digit SIC industry level. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademark)	-0.370					
	(0.444)					
Ln (1+Diversity)		-0.983*				
		(0.076)				
Ln (1+Exploitation)			-1.392***			
			(0.000)			
Ln (1+Exploration)				-0.079		
				(0.903)		
Ln (1+Marketing)					-0.684	
					(0.439)	
Ln (1+Product)						-0.362
						(0.467)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147	147	147	147	147	147
Pseudo R^2	0.285	0.296	0.308	0.279	0.281	0.284

Table 12: Testing the takeover costs channel

This table reports the results of OLS regression analysis for IPO targets' takeover premium. The dependent variable is *Premium*. Column (1) to Column (6) report the results using six product innovation measures: *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*. See Table A1 for details of variable definition. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at the two-digit SIC industry level. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademark)	0.211**					
	(0.030)					
Ln (1+Diversity)		0.200				
		(0.158)				
Ln (1+Exploitation)			-0.093			
			(0.353)			
Ln (1+Exploration)				0.396***		
				(0.002)		
Ln (1+Marketing)					1.213***	
					(0.007)	
Ln (1+Product)						0.197**
						(0.048)
Cash	0.154	0.157	0.187	0.169	0.274*	0.151
	(0.221)	(0.245)	(0.149)	(0.152)	(0.095)	(0.218)
Diversifying	0.122	0.148	0.193	0.070	-0.006	0.128
	(0.810)	(0.773)	(0.695)	(0.890)	(0.989)	(0.801)
Go private	-0.727	-0.675	-0.367	-0.649	-0.651	-0.695
	(0.419)	(0.453)	(0.657)	(0.398)	(0.383)	(0.442)
Deal initiation	-0.110*	-0.091	-0.128**	-0.170*	-0.172*	-0.108*
	(0.097)	(0.178)	(0.048)	(0.059)	(0.051)	(0.095)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127	127	127	127	127	127
R^2	0.549	0.546	0.543	0.559	0.558	0.548

Appendix A: Additional tables

Table A1: Variable definitions

Trademark variables		
Variable	**Definition**	**Source**
Ln (1+Trademark)	The natural logarithm of one plus a firm's granted trademark count in a fiscal year	United States Patent and Trademark Office (USPTO)
Ln (1+Diversity)	The natural logarithm of one plus the number of different categories of granted trademarks of a firm in a fiscal year	United States Patent and Trademark Office (USPTO)
Ln (1+Exploitation)	The natural logarithm of one plus the number of a firm's exploitation trademarks in a fiscal year. An exploitation trademark is defined as trademarks that a firm has already registered at least one trademark in this trademark's class (assigned by the USPTO) over the last 10 years	United States Patent and Trademark Office (USPTO)
Ln (1+Exploration)	The natural logarithm of one plus the number of a firm's exploration trademarks in a fiscal year. An exploration trademark is defined as that the firm has not registered any trademarks in this trademark's class (assigned by the USPTO) over the last 10 years	United States Patent and Trademark Office (USPTO)
Ln (1+Marketing)	The natural logarithm of one plus a firm's marketing trademarks. Following Hsu et al. (2017), a trademark is defined as a marketing trademark if the trademark has no text (i.e., pure logos), or have text comprising four or more words (i.e., advertising slogans)	United States Patent and Trademark Office (USPTO)
Ln (1+Product)	The natural logarithm of one plus a firm's trademarks except its marketing trademarks	United States Patent and Trademark Office (USPTO)
Control variables		
Variable	**Definition**	**Source**
Advertise	Advertising expenses scaled by total assets	Compustat
Age	The difference between a firm's establishment year and IPO year	Dr. Jay Ritter's Website
BHAR	Market-adjusted buy-and-hold return since IPO. BHAR is calculated by the buy-and-hold return of an IPO firm less the buy-and-hold return of the CRSP equal-weighted index starting from the month after the IPO month to the specific	CRSP; Eventus

	month. (the month preceding the acquisition announcement date for IPO targets, or through the relevant fiscal year-end following the IPO year for independent firms	
Cash ratio	Cash balance over total assets	Compustat
HHI	Sum of the squared market share of each firm's total sales in a 3-digit standard industrial classification (SIC) industry of a fiscal year	Compustat
Institutional blockholders	The total ownership percentage of institutional blockholders. A blcokholder is defined as an institutional shareholder that owns at least 5% of the company's shares	Thomson Reuters Institutional (13f) Holdings
IPO proceeds	The logarithm value of IPO gross proceeds	SDC: new issues database
Leverage	Total long-term debt over the value of total assets	Compustat
Liquidity	Current assets scaled by total assets	Compustat
Ln (1+Patent)	The natural logarithm of one plus the total granted patents an IPO firm possesses within the five years prior to the IPO year	National Bureau of Economic Research (NBER) Patent Citation database http://www.patentsview.org
KZ index	Following Lamont, Polk, and Sa'a-Requejo (2001), KZ index is calculated as: -1.001909 × (Cash Flow) + 3.139193 × (Leverage) - 39.36780 × (Dividend) - 1.314759 × (Cash Holdings) + 0.2826389 × (Tobin's q)	Compustat
R&D	Research and development expenses scaled by total assets	Compustat
ROA	EBIT divided by the book value of total assets	Compustat
Sales growth	Percentage growth of total sales	Compustat
Size	The natural logarithm of total assets	Compustat
Tobin's q	Market value of assets divided by the book value of assets. Market value of assets is calculated as: total assets – book value of equity + market value of equity. Market value of equity is calculated by the number of common shares outstanding multiplies the share price	Compustat
Underwriter	Carter and Manaster rank on a scale of 0 to 9	Dr. Jay Ritter's Website
VC	A dummy variable that takes the value of	SDC: new issues database;

	1 if an IPO firm is sponsored by venture capital, and 0 otherwise	SDC: VentureXpert database;

M&A related variables		
Variable	**Definition**	**Source**
Anti-takeover	Five strong anti-takeover provisions in IPOs' corporate charters (Chemmanur, Paeglis, and Simonyan, 2011): staggered boards, poison pills, supermajority required to approve mergers, supermajority required to amend charter or bylaws, and unequal voting rights.	Manually collected from IPO prospectus
Deal initiation	A dummy variable that takes the value of 1 if the target firm initially decides to sell the company and consequently contacts potential buyers, and 0 if at the beginning, a potential buyer approaches the target firm and proposes a M&A transaction	Manually collected from SEC EDGAR company filings
Premium	Deal value minus target's market value of equity, scaled by target's market value of equity. Target's market value of equity 50 days prior to the merger announcement date is used	SDC Mergers & Acquisitions database; CRSP
Cash	A dummy variable that equals 1 if the deal is paid by 100% cash, and 0 otherwise.	SDC Mergers & Acquisitions
Diversifying	A dummy variable that equals 1 if the acquirer and the target have different 2-digit SIC codes and 0 otherwise.	SDC Mergers & Acquisitions
Go private	A dummy variable that equal 1 if the acquirer is a private firm, and 0 if the acquirer is a public firm	SDC Mergers & Acquisitions
M&A activity	Following Schlingemann et al. (2002), M&A activity in a specific industry is measured by the total number of mergers in in an industry divided by the total number of firms in the same industry in Compustat. Industry is defined by 3-digit SIC code. For independent IPOs, the M&A activity is measured in the relevant fiscal year.	SDC Mergers & Acquisitions database; Compustat

Table A2: Predicting the likelihood of becoming IPO targets

This table reports the results of probit regression analysis for predicting the likelihood for an IPO firm of get acquired between 1980 and 2013. The predicted value of the probit regression is taken for propensity score matching analysis. The dependent variable is a dummy variable that equals 1 if the IPO firm gets acquired within the three years after going public, and 0 otherwise. See Table A1 for detailed definition. We report coefficient estimates with *p*-values in parentheses below. *Industry, Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)
Advertise	-0.009
	(0.757)
Age	-0.011*
	(0.067)
BHAR	0.063
	(0.109)
Cash ratio	-0.533*
	(0.095)
HHI	-0.000
	(0.167)
IPO proceeds	0.352***
	(0.003)
KZ index	0.000
	(0.297)
Leverage	-0.305
	(0.454)
Liquidity	0.944**
	(0.015)
Ln (1+Patent)	-0.175
	(0.162)
M&A activity	7.739
	(0.607)
R&D	-0.253
	(0.175)
ROA	-0.676**
	(0.018)
Sales growth	-0.017
	(0.325)
Size	-0.000*
	(0.078)
Tobin's q	-0.019
	(0.257)
Underwriter	0.074*
	(0.068)
VC	0.259
	(0.150)
Industry fixed effect	Yes

Year fixed effect	Yes
State fixed effect	Yes
Observations	1,270
Pseudo R^2	0.293

Table A3: Instrumental variable (IV) analysis (first-stage estimation)

This table reports the results of the first-stage estimation of the two-stage instrumental variable regression analysis that aims to address the potential endogeneity issue of trademarks. The dependent variables in the first-stage estimation are the six proxies of product innovation: *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)* from Column (1) to Column (6) respectively. The IV is *Examiner leniency*, which is the trademark examiner's leniency averaged over all trademark applications submitted by an IPO firm at the IPO stage. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using clustered standard errors at the two-digit SIC industry level. *Industry*, *Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Examiner leniency	3.388***	1.925***	1.637***	2.707***	0.481**	3.311***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.040)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	632	632	632	632	632	632

Table A4: The influence of pre-IPO product innovation and the likelihood of becoming IPO targets (linear probability model)

This table reports the results of cross-sectional OLS regression analysis for independent IPOs and IPO targets between 1980 and 2013. The dependent variable is a dummy variable that equals 1 if the IPO firm gets acquired within the three years after going public, and 0 otherwise. Column (1) to Column (6) report the results using six product innovation measures: *Ln (1+Trademark), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploration), Ln (1+Marketing),* and *Ln (1+Product)*. See Table A1 for a detailed definition. We report coefficient estimates with *p*-values in parentheses below. *p*-values are calculated using double clustered standard errors at the firm and year level. *Industry, Year,* and *State fixed effects* are included. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1+Trademark)	-0.018**					
	(0.012)					
Ln (1+Diversity)		-0.017				
		(0.190)				
Ln (1+Exploitation)			-0.005			
			(0.709)			
Ln (1+Exploration)				-0.022***		
				(0.003)		
Ln (1+Marketing)					-0.015	
					(0.357)	
Ln (1+Product)						-0.019**
						(0.012)
Advertise	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.446)	(0.473)	(0.434)	(0.447)	(0.466)	(0.449)
Age	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.338)	(0.274)	(0.243)	(0.369)	(0.269)	(0.335)
BHAR	0.009*	0.009*	0.009*	0.009*	0.009*	0.009*
	(0.083)	(0.090)	(0.096)	(0.082)	(0.094)	(0.083)
Cash ratio	-0.068*	-0.067*	-0.066*	-0.067*	-0.064*	-0.068*
	(0.061)	(0.066)	(0.070)	(0.065)	(0.076)	(0.060)
HHI	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
	(0.089)	(0.090)	(0.093)	(0.085)	(0.087)	(0.091)
IPO proceeds	0.022**	0.021*	0.020*	0.022**	0.020*	0.022**
	(0.046)	(0.056)	(0.066)	(0.043)	(0.065)	(0.044)
KZ index	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.643)	(0.645)	(0.694)	(0.646)	(0.698)	(0.644)

Leverage	-0.037	-0.035	-0.033	-0.035	-0.033	-0.037
	(0.258)	(0.273)	(0.295)	(0.278)	(0.302)	(0.254)
Liquidity	0.126**	0.123**	0.122**	0.127**	0.121**	0.126**
	(0.013)	(0.015)	(0.016)	(0.012)	(0.016)	(0.013)
Ln (1+Patent)	-0.013	-0.015	-0.016	-0.012	-0.016	-0.013
	(0.407)	(0.333)	(0.299)	(0.460)	(0.317)	(0.399)
M&A activity	-0.107	-0.132	-0.156	-0.114	-0.156	-0.106
	(0.829)	(0.788)	(0.750)	(0.820)	(0.751)	(0.831)
R&D	-0.030**	-0.031**	-0.032**	-0.029**	-0.031**	-0.030**
	(0.041)	(0.033)	(0.028)	(0.047)	(0.033)	(0.041)
ROA	-0.083**	-0.087**	-0.089**	-0.082**	-0.088**	-0.083**
	(0.039)	(0.031)	(0.028)	(0.042)	(0.031)	(0.039)
Sales growth	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.510)	(0.519)	(0.559)	(0.552)	(0.568)	(0.511)
Size	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.647)	(0.662)	(0.660)	(0.641)	(0.639)	(0.654)
Tobin's q	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.006)	(0.008)	(0.009)	(0.006)	(0.010)	(0.006)
Underwriter	0.006**	0.006**	0.006**	0.006**	0.005**	0.006**
	(0.033)	(0.038)	(0.041)	(0.031)	(0.042)	(0.032)
VC	0.029*	0.029	0.028	0.028	0.028	0.029
	(0.099)	(0.100)	(0.109)	(0.106)	(0.104)	(0.101)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,952	1,952	1,952	1,952	1,952	1,952
R^2	0.512	0.511	0.510	0.513	0.510	0.512

Appendix B: Examples of deal initiation (Target-initiated vs. Bidder-initiated)

1. Target-Initiated Deal

"Eli Lilly & Co" acquiring "SGX Pharmaceuticals Inc" Form DEFM14A filed to the SEC on 21/07/2008

"*As a part of the ongoing evaluation of our business, our board and members of our senior management regularly review and assess opportunities to achieve long-term strategic goals. During this ongoing review process, members of our senior management, in conjunction with our board, have considered potential opportunities for acquisitions and other strategic alternatives…At a regularly scheduled board meeting on September 28, 2006, our board agreed to retain Canadian Imperial Bank of Commerce, or CIBC, to provide financial advisory services in connection with our board's review of a range of strategic and financial alternatives, including to help us identify potential merger and acquisition opportunities…Between the third quarter of 2006 and May 2007, CIBC and our board considered more than 60 potential merger and acquisition candidates, and ultimately focused on approximately 30 companies, including Lilly…*"

2. Bidder-Initiated Deal

"Priceline" acquiring "KAYAK" Form S-4 filed to the SEC on 13/12/2012

"*The board of directors of priceline.com from time to time reviews and evaluates potential strategic alternatives with priceline.com's senior management, including possible business combination transactions… In late August 2012, Mr. Boyd contacted Mr. Cutler regarding a meeting with Mr. Hafner and Mr. Cutler to discuss a potential business combination. On August 27, 2012, Mr. Hafner held a conference call with Karen Klein, KAYAK's general counsel, and Bingham McCutchen LLP, referred to as Bingham McCutchen, KAYAK's outside legal counsel, during which priceline.com's interest in a potential business combination was discussed…*

On August 31, 2012, Mr. Boyd, Mr. Hafner and Mr. Cutler met to further discuss a potential business combination between KAYAK and priceline.com. Mr. Boyd also discussed priceline.com's historic approach to acquisitions, including allowing acquired companies to operate independently, having management pay based on the continuing operating results of the acquired company and having management retain an investment in the acquired company. At this meeting, Mr. Boyd discussed the priceline.com operating philosophy, priceline.com's continued interest in KAYAK, and the potential advantages that such a transaction would have to the stockholders of both KAYAK and priceline.com, and to consumers. At this meeting, Mr. Boyd discussed a possible acquisition price of approximately $35.00 per share of KAYAK common stock.