# Trademark and IPO underpricing

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## Abstract

This paper studies the relationship between a firm's pre-IPO trademarks and its IPO underpricing. Using 4,321 US IPOs during the period 1980-2016, we find that firms with a larger number of trademarks prior to the IPO date experience significantly less IPO underpricing. We employ the 1996 Federal Trademark Dilution Act as a quasi-natural experiment and an instrumental variable approach to establish the causality. Our findings are in line with a signaling explanation that trademarks signal firm quality which substitutes the need for underpricing.

JEL Classification: G14, G24, O30, O34

**Keywords**: trademark; IPOs underpricing; information asymmetry; signaling

*"……Google, in the filing for its initial public offering, worried that the term "Google" could one day become synonymous with "search"--resulting in both a loss of trademark protection and reduced brand value. Google's trademark--now the most valuable on the planet, according to Brand Finance--is worth an estimated $44 billion, or 27% of the firm's overall value, measured by market capitalization (its stock price multiplied by the number of shares) ……"*

*By Sean Stonefield, Forebes, Jun 15, 2011*

## 1. Introduction

Together with trade secret, copyright, and patent, trademark is consistently rated as one of the most important intellectual property (IP) within a firm (Jankowski, 2012; Hall, Helmers, Rogers, and Sena, 2014). Despite the importance of trademarking as a firm's business activity, most prior academic research focuses on a firm's patenting activities (He and Tian, 2018). Relatively few studies examine the role of trademarks in the corporate world. One long-standing puzzle in finance is why we observe initial public offering (IPO) underpricing in worldwide capital markets (Boulton, Smart, and Zutter, 2011). That is, why there is a significant discount between the offering price and the first-day closing price. In this paper, we examine whether and how trademarks held by an IPO firm affect IPO underpricing in the United States.

The potential impact of trademarks on IPO underpricing is ex-ante unclear in theory. On one hand, trademarks, like other intangible assets, are not directly recognized in a firm's financial statements. Compared with other types of firm assets (e.g., physical and financial assets), intangible assets are associated with more complex information (Lev, 2000). In terms of trademarks specifically, in the first place, it is not easy to define and enforce property right on trademarks due to the trademark dilution phenomenon (Heath and Mace, 2019).[1] Trademarks are also rarely traded on active and open markets and their economic value (i.e.,

[1] Trademark dilution means that a trademark (or a mark similar enough to confuse customers) can be legally used by an entity other the trademark owner for *non-competing* products or services. Refer to Section 2.1 for more discussions on trademark.

the ability to generate future earnings) is difficult to estimate reliably. Insiders or informed investors may have superior information about the potential value of a firm’s intangible assets. However, in the setting of information asymmetry, it is difficult for outsiders or uninformed investors to determine the value of a firm that holds a large number of trademarks (Gu and Wang, 2005). A well-known explanation for IPO underpricing dating back to Rock (1986) is based on information asymmetry about the IPO firm’s intrinsic value and its fundamental risk. To induce uninformed investors to subscribe stock in companies where they lack full information about the true value of the shares, the issuer compensates these investors in the form of a discount price (Rock, 1986; Chemmanur, 1993). High information complexity and value uncertainty of trademarks thus could potentially exacerbate the information problems among various IPO participants including the firms, underwriters, and investors and consequently lead to a higher underpricing.

Another explanation for the presence of IPO underpricing is the signaling story (Welch, 1989): Underpricing serves as a signal of firm quality to outside investors, which allows the firm to issue equity on better terms at a later date. However, trademarks may signal firm quality as well, which substitutes the need for underpricing. First, as an output of a firm’s late-stage innovation, trademarking activities convey important information on the firm’s new product development and marketing strategy (Gao and Hitt, 2012; Faurel et al., 2019; Block et al., 2014). Moreover, by conferring legal protection on the exclusive use of certain brand names, trademarks prevent potential economic loss from competitors’ imitation (Heath and Mace, 2019). Further, by enabling the firm to differentiate its products/services from its peers, trademarks could grant the firm more competitive advantages and market power, which allows the firm to charge a price premium and earn higher profits (Besen and Raskind 1991; Landes and Posner 1987). Finally, trademarks may serve as collateral to help firms gain more access to finance (Chiu et al., 2019). Therefore, assuming that it is costly to register, maintain and renew trademarks,[2] a firm's trademark portfolio serves as a credible signal of firm quality, which consequently reduces the need for underpricing.

Given that the information effect and signaling effect suggest two opposite conclusions regarding how trademarks affect firm IPO underpricing, we test this unexplored question empirically. To do so, we obtain data on U.S. trademarks from the United States Patent and Trademark office (USPTO) Case files dataset and information on IPO from Thomson-Reuters Securities Data Company (SDC) new issues database from 1980-2016. For each IPO firm, we identify the trademarks registered in the USPTO by it before its IPO date. In our baseline results, we find that the number of a firm's pre-IPO trademarks negatively predicts its subsequent IPO underpricing, after controlling for a variety of firm and issue characteristics. The results are robust when we use various proxies for a firm's trademarking activities, including the quantity, quality, strategy, and type of trademarks. Our baseline results indicate that a firm's trademarks reduce IPO underpricing, suggesting that the signaling effect dominates the information effect.

We recognize that our baseline findings may subject to endogeneity. Although a firm's trademark portfolio is measured using information before the IPO date, which enables our study staying away from reverse causality, our baseline finding may suffer from omitted variable bias. For example, unobservable firm characteristics may simultaneously affect both a firm's stock of trademarks and IPO underpricing. To establish causality, we then employ various econometric techniques to address the endogeneity issues. First, following Heath and Mace (2019) and Chiu et al. (2019), we take advantage of the 1996 Federal Trademark Dilution Act as an arguably exogenous shock to trademark protection, which reinforces the signaling value of trademarks. We find that after the enhanced legal protection on trademark the effect of the trademark on underpricing becomes stronger. Second, we adopt an instrumental variable

[2] There are direct and indirect costs associated with trademarks. Refer to Section 2.1 for more discussions.

approach. Borrowing from the literature that examines patent data,[3] we use trademark examiner leniency as an instrument for an IPO firm's stock of granted trademarks. The negative association between trademarks and IPO underpricing remains in our two-state-least-square (2SLS) analysis. These tests imply a causal interpretation of the negative association between pre-IPO trademarks and IPO underpricing.

Further, we investigate the economic mechanism through which trademarks reduce underpricing. We argue that trademarks reduce IPO underpricing through a substitution effect as a signal for firm quality. We conduct several tests to support this proposed economic channel. First, one key assumption underlying the signaling theory of Welch (1989) is that outside investors do not have full information about firm value.[4] If indeed trademarks impact IPO underpricing through the signaling role, we should observe the effect of the trademark on underpricing is stronger for firms with higher information asymmetry. Our subsample analysis confirms this prediction. Second, we find that our documented effect is more pronounced for firms in more competitive industries. This is perhaps because trademarks enable firms to differentiate their products/services from competitors and help firms lock in price premiums arising from their competitive advantage. Finally, we examine whether a firm's pre-IPO trademarks are able to predict other outcome variables related to the IPO. We find firms hold more trademarks are less likely to withdraw the IPO, delist after the IPO and have better post-IPO long-run operating performance. The results further confirm the signaling role of trademarks since firms with more trademarks do achieve greater success in the long run. Overall, these tests show supportive evidence that trademarks reduce underpricing by signaling firm quality.

[3] Several papers use patent examiner leniency to instrument for the patent grants. See Sampat and Williamns (2019), Farre-Mensa, Hedge, and Ljungqvist (2017), Gaule (2018), Melero, Palomeras, and Wehrheim (2017) and among others.
[4] Welch (1989) assumes that firm owners and investors possess asymmetric information about firm value, while in Rock's (1986) model, the asymmetry is between informed investors and uninformed firm owners and investors.

Our paper contributes to the literature in several dimensions. First, we contribute to the studies that analyze how intellectual property (e.g., patent, copyright, trade secret, and trademark) affects firm outcomes, in particular valuations around IPO. Perhaps because data on trademarks is only publicly available recently (Graham et al., 2013), most earlier studies focus on the role of patents. For example, Heeley, Matusik and Jain (2007) find that patents negatively affect IPO underpricing *only* when the link between patenting and inventive value is transparent. Cao, Jiang, and Ritter (2015) focus on the venture-capital (VC) backed IPOs and show that a firm's pre-IPO patents are able to positively predict its long-run performance after the IPO. Our study deviates from theirs by looking at a firm's trademarks.[5] Different from patents which mainly capture a firm's early stage of technology innovation, trademarks represent the output of a later-stage of innovation and are more associated with a firm's future product development and marketing strategies (Gao and Hitt, 2012; Faurel et al., 2019; Block et al., 2014). Therefore, trademarking activities may better reflect the intention and ability of a firm to commercialize its technology innovation and provide a more reliable signal on a firm's expected future cash flows generated from innovation. These distinctive features explain why we find a much stronger predictive power of trademarks than patents in IPO valuations.

Second, we contribute to the substantial literature on IPO underpricing. Prior studies have documented many determinants of IPO underpricing. Our paper is, in particular, related to studies examine how the quality signal role of the internal and external firm attributes affect IPO outcomes. Prior research have identified various credible signals of firm quality for an IPO firm, such as VC backing (Barry, 1989; Barry et al., 1990; Megginson and Weiss, 1991; Brav

[5] One contemporaneous study by Chemmanur et al. (2018) examines the role of trademarks in entrepreneurial finance. Using VC-backed IPOs, they find that trademarks are associated with a larger amount of VC investment, higher IPO and secondary market valuations, and better post-IPO performance. Our paper differs from theirs by focusing on IPO underpricing and by using the full sample of IPO firms. Given the high cost of IPO underpricing and potential selection-bias of VC investment choice, it is worth investigating the role of trademarks in IPO underpricing using the full sample of IPO firms. Moreover, unlike Chemmanur et al. (2018), our study employs a natural experiment, the 1996 Federal Trademark Dilution Act, as one of our identification strategies, which provides stronger support for a causal interpretation of the findings.

and Gompers, 2003; Bradley and Jordan, 2002), underwriter reputation (Carter, Dark and Singh, 1998; Carter and Manaster, 1990; Loughran and Ritter, 2004), banking relationship (Schenone, 2004), auditor quality (Hogan, 1997; Firth and Liau-Tan, 1998) and innovation activities (Heeley et al, 2007; Guo, Lev, and Shi, 2006; Cao et al., 2015), we add to the literature by considering an important class of intellectual property, trademarks, as another quality signal that shapes IPO underpricing.

The remainder of the paper proceeds as follows. Institutional background and hypothesis development are reported in Section 2. Section 3 describes the sample construction. Section 4 presents the empirical analysis results. We conclude this paper in Section 5.

## 2. Institutional background and hypothesis development

### 2.1 Basics on trademarks

According to the USPTO, a trademark is defined as "*any word, name, symbol, device, or any combination used to or intended to be used to identify and distinguish the goods/services of one seller or provider from those of others*". An easier way to understand the definition is that "a trademark is a brand name". For example, Microsoft Corp registered various brands such as "Microsoft Corp", "Microsoft Office XP", "Windows Phone", and "Surface". They serve to distinguish products of Microsoft from its competitors. When a firm intends to introduce new products or services into the market using a new brand name, it will file a trademark application to the USPTO. The applicant is required to assure that the trademark is not confusingly similar to other registered trademarks. Otherwise. it may lead to a denial of the registration. The registrant also needs to specify the protective coverage of the trademark in the trademark classification system[6] and provide evidence that the trademark has been indeed commercially used in goods-and-services classes specified in the application document. The use-in-commerce requirement is important since it ensures that registered trademarks reflect

[6] Under the NICE classification system, there are 45 classes in total (34 classes for goods and 11 classes for services). The details are provided in https://www.wipo.int/classifications/nice/en/.

products and services that firms were verified to produce and sell (Graham et al., 2013). The main statute of modern trademark law, the 1946 Lanham Act, only provides legal protection for trademarks in their registered classes from infringement by other entities.

Trademarking is reported as the most widely used form of IP protection as it can be applied to any product or service (Hall et al., 2014). According to a survey conducted by the Census Bureau and National Science Foundation in 2015, compared with patents and copyrights, a higher fraction of firms rank trademarks as a very important form of IP protection.[7] Trademarks differ from patents to a great extent. For example, a registered trademark protects your rights to exclusively use the image, logo, phrases, or words to distinguish your goods or services in the market, while a patent protects technological ideas or inventions. The legal protection on a patent typically lasts for a maximum of 20 years starting from its application date, while a trademark may be renewed permanently if it is proved to satisfy the use-in-commerce criterion. Compared with patents that are typically obtained in earlier stages of a firm's innovation process, trademarks indicating the potential introduction of new products/services are generated at the end of the innovation process. Moreover, patents are not feasible in protecting the IP in some sectors, such as service, consumer and retail industries.

To be eligible as a signal of firm quality, trademarks should be costly to acquire. Otherwise, good firms are not able to differentiate themselves by filing trademarks since bad firms can mimic freely. The cost of the registration and maintenance of trademarks is not trivial for a firm. According to the USPTO,[8] for each class that a trademark intends to cover, the application fee is between $225-$400. Since a typical trademark covers more than one class, the total fee for each trademark application could be several thousand dollars. Besides the application fee, it costs a few thousand dollars to maintain a trademark every year as well.

[7] In the survey, 15% of firms rate trademarks as very important, while 11% of firms rate patents as very important. See: https://ncses.nsf.gov/pubs/nsf18313/assets/nsf18313.pdf

[8] See the following USPTO website for details on the trademark fee structure: https://www.uspto.gov/trademark/trademark-fee-information.

Although anyone can apply for a trademark, the application procedures demand significant labor input, such as searching the USPTO trademark database, selecting marks and avoiding the likelihood of confusion, and identifying mark formats and specific classes in coverage. The USPTO thus strongly encourages applicants to hire a trademark attorney for the application process. In addition to the above direct cost associated with trademarks, there are also other indirect costs, such as the opposing and litigation costs. A firm's trademark application is likely to be frivolously opposed by its competitors. According to a proposal to the USPTO,[9] the median cost to an entity in a trademark opposition is $80,000. In addition, the trademark owner is also responsible to monitor potential infringement of its trademarks by rivals and enforce its trademark rights in lawsuits. According to the 2013 Report of the Economic Survey conducted by the American Intellectual Property Law Association,[10] the litigation cost can be as high as two million dollars depending on the issue size. Consistent with the assumption that trademarks are costly to obtain, in our sample, only about 13.1% of firms registered a trademark prior to the IPO.

## 2.2 Recent literature on trademarks

Among various types of corporate intellectual properties, existing finance literature mainly focuses on firms' patenting activities, especially on how internal and external factors shape a firm's quantity and quality of patent output (See He and Tian, 2018). Despite the importance of trademarks in a firm's business activities, their role in corporate finance is less explored. This is perhaps because of the limited access to the comprehensive trademark data (Graham et al., 2013). Recently, a growing body of studies examines the impact of trademarking on firm outcomes in the U.S. For example, Block et al. (2014) find that the number and breadth of trademark applications have inverted U-shaped relationships with the financial valuations of

[9] See: https://tlpc.colorado.edu/wp-content/uploads/2015/05/TMOppositionReform_WhitePaper3.pdf.

[10] See: https://www.aipla.org/detail/journal-issue/2013-report-of-the-economic-survey.

start-ups by venture capitalists. Hsu, Li, Liu, and Wu (2017) find that companies with similar trademarks are more likely to be merged and these deals are associated with higher announcement returns. Regarding trademarks as a proxy for new product development, Faurel et al. (2019) show that trademark creation increases with the value of stock options in CEO compensation. Hsu, Li, Teoh, and Tseng (2018) show that firms with more trademarks experience significantly higher future profitability, larger analyst forecast errors, and higher future abnormal stock returns. One contemporaneous paper that closely related to ours is Chemmanur et al. (2018). Using VC-backed IPO firms, they examine how trademarks affect VC investments and exits, IPO valuations, and post-IPO performance. This paper differs from theirs by looking at IPO underpricing and by examining all the U.S. IPO firms.

To overcome the endogenous nature of a firm's trademarking activities, several studies use the 1996 Federal Trademark Dilution Act as an exogenous shock and study how enhanced trademark protection affects firm outcomes. For example, Heath and Mace (2019) show that stronger trademark protection increases firms' operating profits but has negative effects on firm innovation and product quality. Chiu et al. (2019) find evidence that U.S. public firms use trademarks as collateral to secure bank loans and strengthened trademark protection decreases a firm's cost of bank loans. Overall, these studies suggest that trademarks play an important role in shaping corporate financial policies and valuations.

### 2.3 Trademarks and IPO underpricing

Prior literature has documented substantial evidence that on average initial public offerings are underpriced around the world (Boulton, Smart, and Zutter, 2011). When the offer price is below the close price of the first trading day, the offering is said to be underpriced and the firm has "left money on the table".[11] Although several explanations for the underpricing

[11] According to the most recent presentation by Jay Ritter, from 2009 to 2019 in the U.S. the average amount left on the table is $37 million, which is more than twice the fees paid to underwriters and represents 5% of the post-issue market capitalization of the firm.

phenomenon have been proposed in the literature (Certo et al., 2001), no one could dominate the others, which creates the “underpricing puzzle” in finance research.

One popular explanation for IPO underpricing is based on information asymmetry theory (Rock, 1986). In order to determine the value of an IPO firm, investors rely on firm fundamentals in the prospectus prepared by the new issuer (Bedard et al., 2008; Field and Lowry, 2009). However, because of significant intangible assets, negative cash flows and great technological uncertainty, IPO firms are often characterized by high information asymmetry between existing shareholders (informed), who have superior information about the firm’s expected future cash flows, and potential investors (uninformed), who are willing to share the firm’s ownership and risk. To induce uninformed investors to subscribe stock in companies where they lack full information about the true value of the shares, the issuer compensates these investors in the form of a discount price (Rock, 1986; Chemmanur, 1993).

Trademarks, together with patents and copyrights, represent an important class of a firm’s intangible assets or intellectual property in the US. Although a trademark protects a firm’s brands and logos, it is sometimes difficult to define and enforce the property rights of the trademarks. One notable example is, as we mentioned earlier, the trademark dilution phenomenon, which makes the infringement activities hard to be successfully sued in the court (Heath and Mace, 2019). Moreover, compared to financial and physical assets, the immediate values of trademarks are typically not reflected in a firm’s financial statement and there is great uncertainty regarding whether and how much they will contribute to a firm’s future profit (Lev, 2000). Like most intangible assets, trademarks are not traded on an active and transparent market. Outside investors are thus not able to rely on market prices in estimating the future earning power of the firm. Because of these unique characteristics of trademarks, firms with high trademarking intensity are associated with high information complexity. For example, Gu and Wang (2005) show that firms with more intangible assets are associated with higher analyst forecast error and dispersion, and Hsu, Li, Teoh, and Tseng (2018) confirm this finding using data on trademarks. The presence of a large stock of trademarks may thus increase the information asymmetry and lead to a higher underpricing.

However, on the other hand, another explanation for underpricing implies that trademarks may serve as a substitution for underpricing in signaling firm quality. In Welch's (1989) model, good firms choose costly underpricing to signal their quality and, if successful, recover the cost by selling additional equity at a higher price in follow-up seasonal equity offerings (SEOs). Bad firms, however, are not able to mimic since the market is very likely to detect firm quality after IPO, which prevents them from recovering the loss in the form of underpricing. Unlike patents which mainly capture a firm's early stage of technological innovation, trademarks typically represent output at the end of a firm's innovation progress. A firm's trademarking activities thus contain reliable signal on its new product development, product quality, and marketing strategy in the near future (Gao and Hitt, 2012; Faurel et al., 2019). Moreover, when searching in the product market and making purchase decisions, consumers rely on brand names or trademarks, especially in circumstances where search costs and information asymmetry are high (Gao and Hitt 2012; Graham et al., 2013). Persistent promotion of trademarks helps reduce consumers' search costs, maintain brand awareness and engender loyalty and trust among consumers (Crass, Czarnitzki, and Toole 2019). Trademarks thus assist firms to achieve a competitive advantage by differentiating their products/services from their peers (e.g., Besen and Raskind 1991; Landes and Posner 1987). By conferring legal protection on the exclusive use on the trademark to the owner, trademarks allow the firm to prevent economic loss from competitors' imitation behavior, e.g., using similar marks, images or symbols that can cause customer confusion and erode their market share (Heath and Mace 2019). The consequent market power built upon specific brand names/trademarks enables the firm to charge a price premium and earn higher profits. Finally, trademarks may serve as collateral and help a firm gain more access to bank loan financing (Chiu et al., 2019). These potential benefits may enable trademarks to serve as a reliable signal of firm quality in the IPO process. From this perspective, firms with more trademarks are expected to reduce their need for underpricing to signal firm quality.

Given there are arguments that are both in favor and against IPO underpricing, we propose the main (null) hypothesis in this paper:

*Hypothesis 1: All else equal, a firm's Pre-IPO trademarks do not affect IPO underpricing.*

## 3. Data and Sample

### 3.1 Data

To construct our sample, we start with all the IPO firms from the Thomson-Reuters Securities Data Company (*SDC*) New Issues database. Since prior to 1980 many financial variables of IPO firms in *Compustat* are missing and there is on average a 2-year lag between trademark application date and grant date, we choose to focus our study in the period from 1980 to 2016. Following prior literature (Jain and Kini, 1994; Loughran and Ritter, 2004; Megginson and Weiss, 1991; Heeley et al., 2007), we remove financial firms (SIC 6000-6999), IPOs with proceeds under $1.5 million and with offer price under $5 per share or missing. We also exclude IPOs that correspond to unites offers, spin-offs, limited partnership， and leveraged buyout (LBO). We finally delete observations with incomplete financial information. The details about our sample filtering process are presented in Appendix Table A1.

We download the trademark data from the United States Patent and Trademark Office (USPTO) Trademark Case Files Dataset.[12] This dataset contains detailed information on more than 9 million trademark applications and registrations between January 1870 and February 2018. It maintains information on trademark contents, ownership, classification, date of filing, registration, renewal or abandon, the name of examining attorneys who examine the trademark applications, and so on.[13] Following prior literature, we focus on trademark applications that

[12] The data can be downloaded in the following website:
https://www.uspto.gov/learning-and-resources/electronic-data-products/trademark-case-files-dataset.
[13] Graham et al. (2013) provides a practical description of the USPTO Trademark Case Files Dataset and associated institutional details to facilitate future research using the data.

are successfully registered to ensure that all trademarks we consider are in actual use by the trademark assignees. In our study, the major challenge of using of the USPTO trademark data is to match trademarks assignees to U.S. IPO firms. Similar to Heath and Mace (2019), we implement the matching process as follows: First, we generate a list of names of IPO firms from the *SDC* database. Since a firm may register a trademark under the name of its subsidiaries/branches,[14] we thus supplement all the subsidiaries/branches within a corporate family,[15] which are collected from the LexisNexis Corporate Affiliation Database[16]. Next, for each company name of both parent firm and its subsidiaries, we search in the names of trademark owners in the trademark dataset and try to find the closest one using a fuzzy matching algorithm (Levenshtein Algorithm). Finally, we double-check and manually verify each match to ensure our matching quality using firms' location information. In sum, we are able to successfully match 4,070 registered trademark records[17] to 568 unique U.S. IPO firms between 1980 and 2016.

We obtain first-day trading information for the IPO firms from the Center for Research in Security Prices (*CRSP*) and financial fundamentals such as firm assets, sales, and R&D expenditures in the last financial statement prior to the IPO from *Compustat*. Information on firm founding date and underwriter quality are from Jay Ritter's website (Field and Karpoff, 2002; Loughran and Ritter, 2004). To mitigate the influence of outliers, all continuous variables are winsorized at the 1*st* and 99*th* percentiles and financial variables are adjusted to the dollar value in 2010 using CPI data from the International Financial Statistics provided by

[14] In our sample, about 30% of trademarks are registered under subsidiaries/branches.
[15] Our matching result is slightly different from Heath and Mace (2019) since they obtain subsidiary information from the *CapitalIQ* database, which only covers current information on subsidiaries/branches.
[16] The LexisNexis Corporate Affiliation dataset contains *historical* subsidiary information for more than 18,000 parent firms from 1993 to 2017 in the U.S. For the year before 1993, we use the subsidiary information in 1993 to match with the trademark data.
[17] We only consider the valid trademarks, that is, we exclude trademarks that were registered but expired before the IPO date.

International Monetary Fund (IMF). Detailed definitions of the variables in this paper are given in the Appendix Table A2.

3.2 *Sample Description*

Table 1 presents descriptive statistics. Our final sample consists of 4,321 IPO firms from 1980 to 2016, of which 568 (13.1%) firms have at least one granted trademark prior to their IPO date. As shown in Panel A, the average first-day return is 19.2% for the full sample. On average, a firm has 0.664 trademarks before IPO, the book asset of 181.2 million dollars (in 2010), the firm age of 15.3 years and the IPO proceeds of 89.5 million dollars (in 2010). 46.8% of our firms are venture-backed, and 44.0% are underwritten by prestigious underwriters. In Panel B, we compare the IPO characteristics between firms with at least one trademark and firms without any trademark. The average IPO underpricing of firms that filed at least one trademark before IPO is 3.7% lower than that of firms that never filed any trademark. Moreover, the trademarking sample firms tend to be larger, more mature and raise more money in their IPOs. Taken together, these univariate analyses, in general, suggest a negative relationship between a firm's trademarking activities and its IPO underpricing.

[Insert Table 1 about here]

In table 2, we present the distribution of underpricing and trademarks by industry and year, respectively. As shown in Panel A, there is a large variation in IPO underpricing across different industries. For example, Business Equipment is the most underpriced industry with an average 31.8% first-day stock return, which amounts as much as eight times of the Utilities industry. However, the trademarking intensity of the Business Equipment industry is quite low. Turn to Panel B, similar to the pattern documented by Loughran and Ritter (2004), underpricing of IPOs during 1980-1994 was quite modest and surged during the internet bubble period (1995-2000). However, IPO firms during the bubble period seemed to hold very few trademarks.

[Insert Table 2 about here]

## 4. Empirical results

4.1 Baseline Regression Results

We first present the results from our baseline specification. To examine whether corporate pre-IPO trademark affects US firms' IPO underpricing, we run the following OLS regressions:

$$Underpricing_{i,t} = \beta_0 + \beta_1 * Trademark\ Dummy_i \quad (\text{or } Log\ (1+Trademark_i)) + \beta_2 * Controls + Industry\ Dummy + Year\ Dummy + \varepsilon_i$$

The dependent variable, *Underpricing*, in this model is the IPO underpricing (or first-day stock return). The explanatory variable of our interest is either *Trademark Dummy* (indicating whether an IPO firm holds at least one trademark) or *Log*(*1+Trademark*) (the log of one plus the total number of trademarks an IPO firm holds). Both the two variables are measured at the time of the IPO date. If pre-IPO trademarks reduce IPO underpricing, $\beta_1$ is expected to be negatively significant. We follow existing IPO literature[18] to control for a number of known determinants of IPO underpricing (*Controls*), including whether the firm is backed by venture capital (*VC*), underwriter reputation (*Underwriter*), firm age (*Log (1+Age)*), firm size (*Log (Asset)*), the fraction of retained shares (*Share Overhang*), whether the firm is in high-tech industry (*Tech Dummy*) or in Internet industry (*Internet Dummy*)[19], whether the IPO is listed in Nasdaq exchange (*Nasdaq Dummy*), the total amount of raised proceeds (*Log (Proceeds)*), offer price revision (*Price Revision*), market condition at the time of IPO (*Market Return*) and how hot the IPO activity is in each industry (*Log (1+Hot)*). We also control for the industry and year fixed effects.[20] Robust Standard errors are clustered by industry.

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[18] See Heeley et al., (2007), Loughran and Ritter (2004), Lowry and Shu (2002), Chambers and Dimson (2009), Ljungqvist and Wilhelm (2003), Liu and Ritter (2011), Bradley, Kim, and Krigman (2015) and among others

[19] See Jay ritter's website for the high-tech and internet industry classification: https://site.warrington.ufl.edu/ritter/ipo-data/

[20] In the regressions, we control for industry fixed effect at Fama-French 12 industry level. The results are similar if we use 2-digit (or 3-digit) SIC industry classification.

Table 3 present our baseline regression results. The independent variable is *Trademark Dummy* in Columns (1) and (2) and *Log* (*1+Trademark*) in Columns (3) and (4), respectively. The coefficients estimate for both *Trademark Dummy* and *Log* (*1+Trademark*) are negative and statistically different from zero at the 5% level. In terms of the economic magnitude, trademarking firms (firms with at least one granted trademark filed before the IPO date) experience a 2.6% reduction in IPO underpricing, compared to non-trademarking firms. It represents a 13.5% (2.6%/19.2%) decrease in the first-day return relative to the sample average underpricing of 19.2%, implying that our finding is economically impactful. Overall, our baseline results show that trademarks reduce IPO underpricing and suggest that the signaling effect dominates the information effect.

The estimated coefficients of other control variables are largely consistent with prior literature. For example, larger and older firms are associated with less underpricing. VC-back IPOs, firms in the technology industry, Internet firms, and firms listed in Nasdaq on average are underpriced more.

[Insert Table 3 about here]

4.2 Identification strategy

In the baseline results, we have shown that corporate trademarks prior to the IPO date negatively predict IPO underpricing. Since our trademark measures are calculated on a pre-IPO basis, it is unlikely that our finding is driven by reverse causality, that is, the IPO outcomes should not affect a firm's trademarking performances. However, we recognize that the documented association could be attributed to other unobserved factors. To address potential endogeneity issues, we introduce the 1996 Federal Trademark Dilution Act (FTDA) as a quasi-natural experiment and adopt an instrumental variable approach in the following subsections.

### *4.2.1 The impact of the 1996 Federal Trademark Dilution Act*

The FTDA is aimed to strengthen the protection of "*famous*" trademarks and mitigates the trademark dilution phenomenon[21]. Under the Lanham Act, trademarks are only protected within the range of their registered classes, which are specified when the trademarks are filed. Trademark dilution denotes that a trademark (or a mark similar enough to confuse customers) can be legally used by an entity other than the trademark owner for *non-competing* products or services, i.e., products or serves out of the protected classes of the registered trademark (Mermin, 2000; Morrin, Lee, and Allenby, 2006). To address the prevalent and serious infringement issues incurred by the trademark dilution, the FTDA was enacted by the U.S federal government on 16 January 1996 and was intended to enhance the protection for trademark owners against dilution. In particular, the FTDA extends the protective coverage of famous trademarks to *all* product and service classes. It enables a trademark holder to obtain an injunction without proving actual infringement, but only convincing a judge of the possible confusion (Kim, 2001; Bickley, 2011). In this way, the FTDA effectively enhances the IP protection of trademarks (Heald and Brauneis, 2010). Morrin and Jacoby (2000) document that litigation cases related to trademark dilution increase significantly after 1996. A key limitation of the FTDA is that only "*famous*" trademarks are qualified for the extended protection against likely dilution. However, the FTDA does not give the definition of the term "famous". In practice, whether a trademark is famous or not is judged on a case-by-case basis, which incurs hot debates (Becker, 2000; Dollinger, 2001).

Several recent studies adopt the FTDA as an exogenous shock that increases trademark protection and examine how it affects firm outcomes (Heath and Mace, 2019; Chiu et al, 2019). To build a causal link between trademark and IPO underpricing in our paper, we follow them and conduct tests using the setting of FTDA as a quasi-natural experiment. We hypothesize that

[21] See Heath and Mace (2019) for a detailed discussion.

enhanced trademark protection can strengthen the signaling role played by trademarks. If trademarks indeed reduce firms' IPO underpricing, we should expect the effect is stronger after the enact of FTDA. To test this conjecture, we follow Heath and Mace (2019) and Chiu et al. (2019) and run the following regression for the sub-period 1989-2002:

$$Underpricing_{i,t} = \beta_0 + \beta_1 * PostFTDA_t \times Famous\ Dummy_i + \beta_2 * Famous\ Dummy_i + \beta_3 * Controls + Year\ Dummy + Industry\ Dummy + \varepsilon_i$$

Or

$$Underpricing_{i,t} = \beta_0 + \beta_1 * PostFTDA_t \times Log\ (1 + Famous_i) + \beta_2 * Log\ (1 + Famous_i) + \beta_3 * Controls + Year\ Dummy + Industry\ Dummy + \varepsilon_i$$

Where $PostFTDA$ equals one if the IPO is completed after January 1996 and 0 otherwise. Since the FTDA only affects those famous trademarks, we follow Heath and Mace (2019) and define famous trademarks as trademarks that were registered in 1974 or earlier and were still active on January 16, 1996. Then we construct a variable, $Famous\ Dummy$, which equals 1 if a firm holds at least one famous trademark at the IPO date and 0 otherwise. The variable of our interest is the interaction term $PostFTDA_t \times Famous\ Dummy$, We expect the estimated coefficient $\beta_1$ to be negatively significant.[22] We repeat our regression by replacing $Famous\ Dummy$ with a continuous variable, $Log\ (1 + Famous)$, which is the log of one plus the number of famous trademarks hold by a firm prior to the IPO date.

The results are presented in Table 4. Since we constrain our sample period to 1989-2002, our sample size reduces significantly. Consistent with our conjecture, the coefficients on $PostFTDA_t \times Log\ (1 + Famous_i)$ and $PostFTDA_t \times Famous\ Dummy_i$ are both negatively significant. It means that stronger trademark protection leads to a greater negative

[22] Since the standalone variable $PostFTDA$ is absorbed by the year fixed effect in our regression, it does not appear in our model.

effect of trademarks on IPO underpricing, implying a causal interpretation for the findings in this paper.

[Insert Table 4 about here]

*4.2.2 Instrumental variable approach*

To further alleviate that our baseline finding is likely driven by some omitted factors, we perform an instrumental variable approach and conduct Two-Stage Least Square (2SLS) analysis in this section. Similar to studies using patent data (See Sampat and Williamns, 2019; Farre-Mensa, Hedge, and Ljungqvist, 2017; Gaule, 2018; Melero, and Palomeras, and Wehrheim, 2017), we instrument for the trademark grants using trademark examiner's leniency. Trademark applications are assigned to examiners in a quasi-random fashion. Upon assigned to review trademark applications, examiners differ systematically in their propensity to approve trademarks. For example, examiners with a higher (lower) level of leniency are more likely to accept (reject) the application. Thus, examiner leniency should be relevant for a firm's granted trademarks. It is also unclear how examiner leniency would affect IPO underpricing through ways other than a firm's trademarking activities.

To construct our instrument variable, we first calculate a time-varying proxy for the leniency of each *individual* examiner (the approve rate of examiner *j* assigned to review a trademark application *k* made by firm *i* in year *t*) as follow[23]:

$$Individual\ Examiner\ Leniency_{j,k,i,t} = \frac{Grant_{j,t} - Grant_{k,i,t}}{Application_{j,t} - 1}$$

Where $Grant_{j,t}$ and $Application_{j,t}$ are the number of trademarks granted and application reviewed by examiner *j* in year *t* and $Grant_{k,i,t}$ equals one if the application *k* made by firm *i* in year *t* is approved and 0 otherwise.. Since we need a *firm-level* instrument for the number of

[23] Since the number of trademarks granted to a firm before going public is quite limited, the estimation for individual examiner's leniency could possibly be biased significantly. We thus take advantage of information on trademarks granted to all public firms to calculate this measure.

trademarks granted to an IPO firm, we follow the literature by taking the average leniency of all trademark applications that firm *i* has filed before the IPO date:[24]

$$Avg\ Leniency_i = \frac{1}{n_i}\sum_j Individual\ Examiner\ Leniency_{j,k,i,t}$$

We conduct the 2SLS analysis and present the results in Table 5. As shown in Columns (1) and (2), in the first stage, examiner leniency is positively related to a firm's granted trademarks. The *F*-statistic is larger than 10 in Column (2), reject the null of a weak instrument. After instrumentation, in Columns (3) and (4), the coefficients on the predicted value of our trademark measures are negative and statistically significant. Taken together, the 2SLS regression results provide us with greater confidence that pre-IPO trademarks causally affect IPO underpricing.

[Insert Table 5 about here]

### 4.3 More nuanced trademark proxies

In the above analysis, we have shown that the quantity of a firm's trademarks has a significant impact on IPO underpricing. In this part, we examine additional nuanced proxies related to trademarks.

We first look at the quality of a firm's trademarks. Trademarks existing for more years tend to be of better quality (Hsu, Li, Liu, and Wu, 2017). To measure the trademark quality, we calculate IPO firms' average age of each trademark as the log of one plus the difference between IPO year and the trademark application year (*Log (1+Trademark Age)*). We further calculate the log of the number of famous trademarks (*Log* (*1+Famous*)) following Heath and Mace (2019). The two variables capture the quality of an IPO firm's trademark portfolio. We also construct two dummy variables, *Trademark Age Dummy*—which equals one for firms with

[24] For firms without any trademark, the value of this variable is missing and these firms are not included in our 2SLS analysis. We also drop firms with missing names of trademark examiners, which leaves us with 552 IPO firms.

above the sample median *Trademark Age* and zero otherwise, and *Famous Dummy*—which equals one for firms with at least one famous trademark before IPO and zero otherwise. The results are presented in Panel A of Table 6. Most of the coefficients on the quality proxies are negatively significant. It suggests that, besides the quantity of a firm's trademark holding, the quality also matters for underpricing.

We also study whether different trademarking strategies, such as trademark diversity and trademark explorativeness, affect the underpricing differently. Following Hsu, Li and Nozawa (2018) and Hsu, Li, Teoh, and Tseng (2018), *Trademark Diversity* is the log of one plus the total number of unique classes that a firm's trademark portfolio covers. *Log* (*1+Exploration*) and *Log* (*1+Exploitation*) represent the number of explorative trademarks and exploitative trademarks held by an IPO firm, respectively. A trademark is defined as an explorative one if the firm has not registered any trademarks in this trademark's class (assigned by the USPTO) over the last 10 years. Otherwise, the trademark is defined as an exploitative trademark. As shown in Panel B of Table 6 we find that firms with more diversified and explorative trademarks are associated with less IPO underpricing, while we do not find a significant association between exploitative trademarks and underpricing.

Finally, we separate all trademarks into product trademarks and marketing trademarks according to their types. Following Hsu et al. (2017), we defined a trademark as a marketing trademark if the mark has no text (i.e., pure logos), or have text comprising four or more words (i.e., advertising slogans). The rest are defined as product trademarks. In Panel C of Table 6, we find both of the two types of trademarks are negatively associated with underpricing. In sum, we find consistent and robust results when using these more nuanced measures for a firm's trademarking activities.

[Insert Table 6 about here]

### 4.4 Economic channel

In the above analysis, we have shown robust evidence that pre-IPO trademark has a significantly negative impact on IPO underpricing. Now, in this part, we further investigate the economic channels through which trademark affects IPO underpricing. We propose that trademarks reduce underpricing since it can signal firm quality. In this section, we seek to provide supportive empirical evidence to this argument.

#### *4.4.1 The impact of information asymmetry*

One key assumption behind Welch's (1989) signaling model is that there exists information asymmetry between firm owners and outside investors. If there is no information asymmetry and outside investors have complete information on firm intrinsic value, the IPO firm has no incentive to use underpricing or trademarks to signal firm quality. On the contrary, if information asymmetry is severe, the incentive to signal becomes strong. Thus, the importance of the signaling role played by a firm's trademarks increases with the level of a firm's information asymmetry (Leland and Pyle,1977; Amit, Glosten, and Muller, 1990; Cao and Hsu, 2011). Motivated by this rationale, we expect that the negative association between trademark and IPO underpricing should be more pronounced for firms with greater information asymmetry.

To test this conjecture, we borrow four proxies for private firms' information asymmetry in the literature. First, following Leary and Roberts (2010) and Zhang (2006), we measure a firm's information environment using firm sales and firm age. Small and young firms are less diversified and have less information available to the market. Second, we measure information asymmetry based on a firm's R&D expenses following Aboody and Lev (2000) and Sufi (2007). They show that firms with high R&D intensity tend to be more opaque. Finally, we construct an industry-level measure relying on the information environment of public firms that are in the same industry as the IPO firm. In particular, we calculate the return residual volatility based on the Fama-French three factors model (Blackwell, Marr, and Spivey, 1990; Clarke, Fee, and Thomas, 2004; Cao and Hsu, 2011).[25] Using the above four proxies, we conduct subsample analysis and check if the effect of trademarks on IPO underpricing is different between high- and low- information asymmetry firms.

We present the results in Table 7. The subsamples are divided according to whether the value of the four proxies is above the sample median or not. We find consistent results that the negative impact of trademarks on IPO underpricing is only significant for firms with severe information asymmetry problems (i.e., young firms, small firms, firms with intensive R&D activities and firms in industries with high return residual volatility). The Wald test indicates that the difference in the coefficients between the two subsamples is also negatively significant. The subsample tests suggest that trademarks are more effective in reducing IPO underpricing when information asymmetry is high, which is in line with our conjecture.

[Insert Table 7 about here]

*4.4.2 The impact of product market competition*

One of the benefits of trademarking is to insulate competition (Heath and Mace, 2019). By exclusively own the legal use of certain brand names, trademarking can assist a firm to charge a higher price premium, to differentiate its products, and to prohibit imitation by its competitors. Trademarking thus can gain the firm more competitive advantages in the product market (Chamberlin, 1933). The intensity of competition that an IPO firm is confronted is likely to increase the protective value of trademarks and strengthen the signaling role played by a firm's trademarks. We thus conjecture that the negative effect of trademarks on underpricing should be stronger for IPO firms in more competitive industries.

[25] We construct the measure of return residual volatility based on the following process. First, for each public stock, we regress its daily excess returns on market excess returns, the small-minus-big factor, and the value-minus-growth factor as Fama and French (1993), and then estimate the regression residuals. Second, we compute the variance of each individual stock's return residuals as the firm-level return residual volatility. Finally, for each industry (2-digit SIC), we calculate the average volatility of all the firms within the industry.

To test our prediction, we measure the competitive environment that an IPO firm faces using the Herfindahl-Hirschman Index (*HHI*) of sales of *public* firms within the same industry (3-digit SIC). An industry is considered to be highly competitive if its *HHI* is above the sample median in the year prior to the IPO date. We conduct subsample analysis and the results are presented in Table 8. The negative effect of trademarks on underpricing is only significant for firms in highly competitive industries. The Wald test also indicates the difference in the coefficients between industries with high- and low- competition is negatively significant. The results are consistent with our prediction that the impact of trademarks on IPO underpricing is more pronounced for firms in more competitive industries, which again confirm our signaling channel.

[Insert Table 8 about here]

*4.4.3 Evidence from other IPO outcomes*

We argue that trademarks benefit a firm in various ways, including help firms enhance customer loyalty, lock in monopoly rents, secure bank loan financing and so on. In this part, we test how pre-IPO trademarks predict other outcome variables related to the IPO, including the probability of IPO withdrawal, IPO delisting, and post-IPO long-run performance. If trademarks do signal firm quality, we should observe they are able to positively predict post-IPO long-run performance but negatively predict IPO withdrawal and delisting.

We first test whether the pre-IPO trademarks are able to predict a firm's probability of IPO withdrawal. To do so, we include both successful and failed IPOs and use a dummy variable to indicate the deal status (successful or withdrawn). Since financial data for failed IPOs is quite limited, we are only able to control *Underwriter, Tech Dummy, Internet Dummy, Nasdaq Dummy, Market Return*, and *Log* (*1+Hot*) in this test. We further test another two performance measures after the IPO. One is whether the IPO firm gets delisted and the other is post-IPO long-run performance. We construct an indicator, which equals one if the IPO firm delisted within 5 years after the IPO and otherwise zero. To measure the post-IPO performance, we follow Ritter (1991) and Jain and Kini (1994) and calculate the monthly market-adjusted return over 36 months after the IPO (*Return_Adj*) and the return on assets (*ROA*) in the third fiscal year after the IPO.

The results are presented in Table 9. Consistent with our expectation, pre-IPO trademarks negatively predict the probability of IPO withdrawal and IPO delisting, but positively predict post-IPO long-run performance. These results again confirm the signaling role played by trademarks.

[Insert Table 9 about here]

## 4.5 Robustness Checks

### *4.5.1 Propensity Score Matching*

Since most firms do not possess any trademark before going public, to balance our sample, we adopt the Propensity Score Matching (PSM) technique as a robustness check. First, we regress our proxy for trademarks against several matching variables, including *VC, Underwriter*, and *Log (Asset)*, and calculate the propensity score based on a Logit regression model. For each firm that has at least one trademark (*Trademark Dummy*=1), we find a matched (control) firm without any trademark (*Trademark Dummy*=0) with the nearest score and re-run our baseline regression using the matched sample.

In Table 10 Panel A, we first show that there is no significant difference in our matching variables between the treatment and control group. The regression results using the matched sample are presented in Panel B. Although the sample size shrinks significantly, we still find trademarks have a negative impact on IPO underpricing and the economic magnitude is close to that reported in our baseline regression. The PSM analysis reinforces our main results that trademarks act as an effective signal to reduce firms' IPO underpricing.

[Insert Table 10 about here]

*4.5.2 Remove the confounding effect of patenting activities*

Although both trademarks and patents serve as important classes of a firm's intangible assets or intellectual properties, as we mentioned earlier, they exhibit great distinctions. Since a firm's trademarks may positively correlate with its patenting activities, that is, firms with more trademarks are likely to possess more patents, it is likely that our findings are driven by a firm's patenting activities. To disentangle the confounding effect of patents, we conduct more tests in this part.

First, we attempt to control for a firm's patenting output to see if trademarks could have an incremental effect on underpricing. We collect information on public firms' patents from the NBER Patent Database and calculate the number of patents that an IPO firm filed and eventually granted prior to the IPO date (*Log* (*1+Patent*)). Since the patent data from NBER ends at 2006, we have to focus our tests in a sub-period between 1980 and 2006 in this section. As shown in Column (1) in Table 1, the coefficient on *Log (1+Patent)* is not significant, which is consistent with Heeley et al. (2007)'s finding that a firm's overall stock of patents has no effect on underpricing. In Columns (2) and (3), after controlling for a firm's patent holdings, we still find a significant negative relation between trademarks and underpricing. To further remove the confounding effect of patents, we conduct tests by focusing on a subsample of firms that haven't file any patents but registered at least one trademark prior to the IPO. After imposing this restriction, we are left with only 443 IPO firms. However, our baseline finding still holds in this much smaller sample. To sum, the negative effect of trademarks on underpricing is unlikely to be explained by the patenting activities.

[Insert Table 11 about here]

## 5. Conclusion

In this study, we examine how trademarks hold by an IPO firm affect IPO underpricing in the United States. We find robust evidence that trademarks negatively predict the underpricing. Consistent with Welch's (1989) signaling theory, we argue that trademarks signal firm quality and substitute the demand for underpricing. To establish causality, we exploit the 1996 Federal Trademark Dilution Act as a quasi-natural experiment and an instrumental variable approach. The results support our causal interpretation. We further find that the effect of trademarks on underpricing is stronger for firms with higher information asymmetry and firms in more competitive industries. Trademarks also positively predict other IPO-related performance measures. These empirical findings support our argument that trademarks reduce underpricing by signaling firm quality.

Overall, our paper contributes to the IPO literature by showing that trademarks are an important determinant of a firm's IPO underpricing. Our study also contributes to the emerging literature that studies the impact of trademarks on firm outcomes. Since trademark is an essential type of corporate intangible asset but not recognized in a firm's financial statement, our findings can help investors better understand the valuation of an IPO firm.

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## Appendix

### Table A1. Sample Selection Criteria

| Sample selection Step | | Number of firms |
|---|---|---|
| Total number of US common-stock IPOs in SDC database | | 13,533 |
| Less: IPOs with proceeds under $1.5 million | | (706) |
| Less: IPOs with offer price under $5 per share or missing | | (1,113) |
| Less: Unit offers, Spin-offs, limited partnership, ADRs, LBO, REITs, Close-end fund and financial institutions | | (4,731) |
| | Subtotal: | 6,983 |
| Less: Observation lacking values for the first-day close price | | (871) |
| Less: Other observation lacking values for control variables | | (1,791) |
| | Final Sample | 4,321 |

## Table A2. Variable Definitions

| Variable | Definition | Data Source(s) |
|---|---|---|
| | ***Trademark characteristics*** | |
| Log (1+ Trademark) | The log of one plus the total number of granted trademarks that a firm has filed prior to the IPO. | USPTO |
| Trademark Dummy | Equals 1 if the firm has at least one granted trademark filed before the IPO and 0 otherwise. | USPTO |
| Log (1+ Trademark Age) | The log of the average age (the difference between IPO year and trademark application year) of all trademarks in a firm's portfolio at the time of IPO date. | SDC, USPTO |
| Trademark age Dummy | Equals 1 if the average age of all trademarks in a firm's portfolio is larger than the median of all the IPO firms, and 0 otherwise. | SDC, USPTO |
| Log (1+ Famous) | The log of one plus the number of famous trademarks that a firm has filed for prior to the IPO. A famous trademark is defined as a trademark that registered in 1974 or earlier and was still active on the IPO date. | USPTO |
| Famous Dummy | Equals 1 if a firm holds at least one famous trademark before the IPO and 0 otherwise. | USPTO |
| Trademark Diversity | The log of one plus the total number of unique trademark classes of trademarks filed by a firm before IPO. | USPTO |
| Log (1+ Exploration ) | The log of the sum of exploratory trademarks filed before IPO. A trademark is defined as an exploratory one if the firm has not registered any trademark in this trademark's class over the last 10 years. | USPTO |
| Log (1+ Exploitation) | The log of the sum of exploitative trademarks filed before the IPO. A trademark is defined as an exploitative one if the firm has already registered at least one trademark in this trademark's class over the last 10 years. | USPTO |
| Log (1+ Product) | The log of one plus the number of product trademarks that the firm has filed prior to the IPO. | USPTO |
| Log (1+ Marketing) | The log of one plus the number of marketing trademarks that the firm has filed prior to the IPO. | USPTO |
| | **IPO characteristics** | |
| Underpricing | IPO underpricing, calculated as the first-day stock return: (close price-offer price)/offer price. | CRSP, SDC |
| Return_Adj | Cumulative market-adjusted monthly returns over 3 years after the IPO date. | CRSP |
| ROA | Return on assets, defined as operating income before depreciation scaled by total assets. | COMPUSTAT |
| IPO Withdrawn | Equals 1 if an IPO is withdrawn and 0 otherwise. | SDC |
| IPO Delisting | Equals 1 if a firm is delisted within five years period after the IPO and 0 otherwise. | CRSP |
| VC | The indicator variable for venture-capital backed IPO firms. | SDC |
| Underwriter | Equals 1 if the underwriter reputation score is equal to or greater than 8. The reputation score is according to Loughran and Ritter's (2004). | Ritter's website |
| Log (1+ Age) | The log of firm age, which is the difference between firm IPO year and founding year. | Ritter's website |
| Log (Asset) | The log of book asset measured in the last financial statement prior to the IPO (inflation-adjusted in millions of 2010 dollars). | COMPUSTAT |
| Share Overhang | The ratio of retained shares to the public float. | SDC |
| Tech Dummy | Equals 1 if an IPO firm is in the technology business and 0 otherwise. | Ritter's website |
| Internet Dummy | Equals 1 if an IPO firm is in the Internet business and 0 otherwise. | Ritter's website |
| Nasdaq Dummy | Equals 1 if an IPO firm is listed at Nasdaq exchange. | SDC |
| Log (Proceeds) | The log of the total amount of money raised in the IPO from investors in millions (inflation-adjusted in millions of 2010 dollars). | SDC |
| Price Revision | The percentage change from the amended mid-point of the offer price range to the offer price. | SDC |
| Market Return | Compounded value-weighted market return over 20 calendar days before the IPO date. | CRSP daily |
| Log (1+ Hot) | The log of one plus the number of IPOs in the same industry as the IPO firm in the preceding year. | SDC |
| | **Other variables** | |
| PostFTDA | Equals 1 if the IPO year is in or after 1996 and 0 otherwise | SDC |
| Examiner Leniency | Examiner leniency averaged over all the trademark applications filed by a firm prior to the IPO | USPTO |
| Log (1+ Patent) | The log of one plus the number of granted patents that a firm has filed for prior to the IPO. | NBER |

## Table 1 Descriptive Statistics

This table reports the descriptive statistics. Panel A provides the summary statistics of main variables in this paper. Panel B provides descriptive statistics for trademarking and non-trademarking sample separately. The sample contains U.S. IPO firms in SDC database from 1980 to 2016. All continuous variables are winsorized at 1% and 99% levels. Detailed variable definitions are provided in the Appendix Table A2.

Panel A Summary statistics

| Variables | Observations | Mean | Median | Min | Max | Std |
|---|---|---|---|---|---|---|
| Underpricing | 4,321 | 0.192 | 0.079 | -0.167 | 2.018 | 0.346 |
| Trademark | 4,321 | 0.664 | 0.000 | 0.000 | 17.000 | 2.515 |
| Famous trademark | 4,321 | 0.058 | 0.000 | 0.000 | 3.000 | 0.382 |
| VC | 4,321 | 0.468 | 0.000 | 0.000 | 1.000 | 0.499 |
| Underwriter | 4,321 | 0.440 | 0.000 | 0.000 | 1.000 | 0.496 |
| Firm age | 4,321 | 15.268 | 8.000 | 0.000 | 95.000 | 19.199 |
| Asset | 4,321 | 181.210 | 36.982 | 0.695 | 3597.580 | 485.496 |
| Share overhang | 4,321 | 3.054 | 2.585 | -0.501 | 11.863 | 2.066 |
| Proceeds | 4,321 | 89.490 | 52.362 | 5.968 | 760.413 | 120.729 |
| Price revision | 4,321 | -0.006 | 0.000 | -0.375 | 0.333 | 0.131 |
| Market return | 4,321 | 0.008 | 0.009 | -0.068 | 0.073 | 0.028 |
| Hot market | 4,321 | 21.960 | 9.000 | 0.000 | 213.000 | 35.393 |
| Nasdaq dummy | 4,321 | 0.706 | 1.000 | 0.000 | 1.000 | 0.456 |
| Tech dummy | 4,321 | 0.402 | 0.000 | 0.000 | 1.000 | 0.490 |
| Internet dummy | 4,321 | 0.083 | 0.000 | 0.000 | 1.000 | 0.276 |

Panel B: Trademarking *v.s.* non-trademarking samples

| Variables | Trademark dummy=1 (*N*=568) | Trademark dummy=0 (*N*=3753) | Difference (1)-(2) | t-value |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Underpricing | 0.160 | 0.197 | -0.037** | -2.379 |
| Trademark | 5.048 | 0.000 | 5.048*** | 60.659 |
| VC | 0.535 | 0.458 | 0.077*** | 3.451 |
| Underwriter | 0.444 | 0.439 | 0.005 | 0.203 |
| Firm age | 17.298 | 14.961 | 2.337*** | 2.705 |
| Asset | 187.824 | 180.209 | 7.615 | 0.348 |
| Share overhang | 3.577 | 2.975 | 0.602*** | 6.513 |
| Proceeds | 95.494 | 88.582 | 6.912 | 1.272 |
| Price revision | -0.010 | -0.005 | -0.005 | -0.878 |

## Table 2 Sample Distribution

This table reports the industry and year distribution of IPO average underpricing and trademark. The sample contains U.S. IPO firms in the SDC database from 1980 to 2016. The industry classification is based on the Fama French 12 industry classifications. Detailed variable definitions are provided in the Appendix Table A2.

Panel A: Industry distribution of IPO average underpricing

| Industry | # of IPO | Mean | | |
|---|---|---|---|---|
| | | IPO Underpricing | Trademark dummy | Log (1+Trademark) |
| 1: Consumer NonDurables | 188 | 0.138 | 0.138 | 1.479 |
| 2: Consumer Durables | 98 | 0.089 | 0.224 | 1.969 |
| 3: Manufacturing | 339 | 0.091 | 0.124 | 1.050 |
| 4: Enrgy | 109 | 0.049 | 0.028 | 0.110 |
| 5: Chemicals and Allied Products | 62 | 0.114 | 0.242 | 2.710 |
| 6: Business Equipment | 1,394 | 0.318 | 0.165 | 0.664 |
| 7: Telecom | 163 | 0.185 | 0.061 | 0.160 |
| 8: Utilities | 30 | 0.040 | 0.133 | 0.300 |
| 9: Shops | 552 | 0.130 | 0.134 | 0.763 |
| 10: Health | 758 | 0.125 | 0.115 | 0.377 |
| 12: Others | 628 | 0.179 | 0.088 | 0.306 |
| Total | 4,321 | | | |

Panel B: Year distribution of IPO average underpricing

| Year | # of IPO | Mean | | |
|---|---|---|---|---|
| | | IPO Underpricing | Trademark dummy | Log (1+Trademark) |
| 1980 | 33 | 0.185 | 0.364 | 2.970 |
| 1981 | 87 | 0.083 | 0.161 | 0.345 |
| 1982 | 32 | 0.142 | 0.281 | 1.688 |
| 1983 | 201 | 0.125 | 0.244 | 1.159 |
| 1984 | 84 | 0.043 | 0.214 | 0.774 |
| 1985 | 95 | 0.065 | 0.242 | 1.211 |
| 1986 | 200 | 0.070 | 0.275 | 1.635 |
| 1987 | 147 | 0.080 | 0.272 | 2.027 |
| 1988 | 56 | 0.070 | 0.446 | 2.107 |
| 1989 | 60 | 0.096 | 0.400 | 3.317 |
| 1990 | 61 | 0.126 | 0.295 | 2.164 |
| 1991 | 150 | 0.114 | 0.173 | 1.500 |
| 1992 | 218 | 0.102 | 0.083 | 0.913 |
| 1993 | 282 | 0.135 | 0.004 | 0.060 |
| 1994 | 240 | 0.109 | 0.004 | 0.071 |
| 1995 | 268 | 0.212 | 0.004 | 0.019 |
| 1996 | 224 | 0.203 | 0.004 | 0.076 |
| 1997 | 236 | 0.156 | 0.013 | 0.161 |
| 1998 | 141 | 0.221 | 0.021 | 0.043 |
| 1999 | 281 | 0.698 | 0.004 | 0.007 |
| 2000 | 219 | 0.529 | 0.187 | 0.420 |
| 2001 | 37 | 0.203 | 0.027 | 0.027 |
| 2002 | 38 | 0.095 | 0.158 | 0.526 |
| 2003 | 43 | 0.111 | 0.023 | 0.070 |
| 2004 | 116 | 0.128 | 0.172 | 0.474 |
| 2005 | 95 | 0.103 | 0.084 | 0.137 |
| 2006 | 96 | 0.120 | 0.125 | 0.302 |
| 2007 | 104 | 0.157 | 0.135 | 0.404 |
| 2008 | 14 | 0.080 | 0.143 | 0.500 |
| 2009 | 33 | 0.114 | 0.182 | 1.788 |

| | | | | |
|---|---|---|---|---|
| 2010 | 57 | 0.089 | 0.158 | 0.561 |
| 2011 | 53 | 0.150 | 0.396 | 1.472 |
| 2012 | 58 | 0.175 | 0.362 | 1.224 |
| 2013 | 82 | 0.248 | 0.293 | 1.122 |
| 2014 | 99 | 0.186 | 0.253 | 0.475 |
| 2015 | 58 | 0.200 | 0.259 | 0.534 |
| 2016 | 23 | 0.120 | 0.000 | 0.000 |
| Total | 4,321 | | | |

## Table 3 Baseline Regression Results

This table reports the results from our baseline regressions. The dependent variable is IPO underpricing, the independent variable is *Trademark Dummy* in Columns (1) to (2) and *Log(1+Trademark)* in Columns (3) to (4). Detailed variable definitions are provided in the Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level.

| Variables | Underpricing | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Trademark Dummy | -0.024** | -0.026** | | |
| | (-2.426) | (-2.678) | | |
| Log (1+Trademark) | | | -0.016** | -0.017** |
| | | | (-2.414) | (-2.465) |
| VC | 0.035** | 0.025** | 0.035** | 0.025** |
| | (2.715) | (2.639) | (2.725) | (2.623) |
| Underwriter | 0.000 | -0.017*** | 0.000 | -0.017*** |
| | (0.012) | (-3.589) | (0.005) | (-3.604) |
| Log(1+Age) | -0.016*** | -0.012*** | -0.016*** | -0.012*** |
| | (-5.506) | (-3.914) | (-5.412) | (-3.738) |
| Log(Asset) | -0.007 | -0.022** | -0.006 | -0.021** |
| | (-1.801) | (-2.926) | (-1.771) | (-2.920) |
| Share Overhang | 0.036*** | 0.033*** | 0.036*** | 0.033*** |
| | (3.866) | (4.363) | (3.872) | (4.365) |
| Tech Dummy | 0.044** | 0.038** | 0.044** | 0.038** |
| | (2.784) | (2.415) | (2.754) | (2.399) |
| Internet Dummy | 0.205*** | 0.166*** | 0.205*** | 0.166*** |
| | (6.085) | (5.063) | (6.091) | (5.072) |
| Nasdaq Dummy | 0.007 | 0.012* | 0.007 | 0.012* |
| | (0.702) | (1.962) | (0.685) | (1.927) |
| Log (Proceeds) | | 0.039** | | 0.040** |
| | | (2.883) | | (2.863) |
| Price Revision | | 0.755*** | | 0.754*** |
| | | (7.673) | | (7.667) |
| Market Return | | 0.774*** | | 0.778*** |
| | | (3.207) | | (3.232) |
| Log (1+Hot) | | -0.002 | | -0.002 |
| | | (-0.259) | | (-0.244) |
| Industry fixed effect | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Observations | 4,321 | 4,321 | 4,321 | 4,321 |
| R-squared | 0.336 | 0.430 | 0.336 | 0.430 |

## Table 4 The impact of the 1996 Federal Trademark Dilution Act

This table reports the results of the impact of the 1996 Federal Trademark Dilution Act using sample period from 1989-2002. The dependent variable is IPO underpricing, the explanatory variable of interest is the interaction term between *PostFTDA* and *Famous Dummy* (or *Log(1+Famous)*). $PostFTDA$ equals one if the IPO is completed after January 1996 and otherwise 0. $Log\ (1 + Famous)$ is the log of one plus the number of famous trademarks (registered earlier than 1974 and was still active on January 16, 1996) held by a firm prior to the IPO date. $Famous\ Dummy$ equals 1 if a firm holds at least one famous trademark at the IPO date and 0 otherwise. All baseline controls from Table 3 column (2) are included in regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in the Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level.

| | Underpricing | |
|---|---|---|
| Variables | (1) | (2) |
| Famous Dummy × PostFTDA | -0.115** | |
| | (-2.326) | |
| Famous Dummy | -0.020 | |
| | (-0.816) | |
| Log(1+Famous) ×PostFTDA | | -0.086* |
| | | (-1.734) |
| Log(1+Famous) | | -0.013 |
| | | (-0.622) |
| Baseline control | Yes | Yes |
| Industry fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Sample Period | 1989-2002 | 1989-2002 |
| Observations | 2,455 | 2,455 |
| R-squared | 0.405 | 0.405 |

## Table 5 Two-Stage-Least-Square Analysis

This table reports the regression results of the 2SLS analysis. We use trademark examiner leniency as the instrumental variable for trademarks. Columns (1) and (2) report the first-stage regression results, with *Trademark Dummy* and *Log(1+Trademark)* as the dependent variable, respectively. Results from the second-stage regressions are reported in Columns (3) and (4), with IPO underpricing as the dependent variable. The independent variable in the first-stage regression is *Examiner Leniency*. The independent variable in the second-stage is the predicted values of *Trademark Dummy* or *Log(1+Trademark)* from the first-stage regressions. All baseline controls from Table 3 Column (2) are included in all regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in the Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level.

| Variables | First Stage | | Second Stage | |
|---|---|---|---|---|
| | Trademark Dummy | Log(1+Trademark) | Underpricing | |
| | (1) | (2) | (3) | (4) |
| Examiner Leniency | 0.419*** | 2.133*** | | |
| | (3.093) | (5.969) | | |
| Predicted Trademark Dummy | | | -0.862** | |
| | | | (-2.544) | |
| Predicted Log(1+Trademark) | | | | -0.169*** |
| | | | | (-2.934) |
| Baseline controls | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| F-Statistics | 9.56 | 35.63 | | |
| Prob>F | 0.003 | 0.000 | | |
| Observations | 552 | 552 | 552 | 552 |
| R-squared | 0.184 | 0.424 | | |

## Table 6 More nuanced measures on trademarks

This table examines the relation between trademark characteristics and IPO underpricing using several more nuanced measures on trademarks. The explanatory variables in Panel A, Panel B, and Panel C are proxies for trademark quality, trademark strategy, and trademark type, respectively. The dependent variable is IPO underpricing. All baseline controls from Column (2) in Table 3 are included in the regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in the Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level.

Panel A: Trademark quality

| Variables | Underpricing | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log (1+Trademark Age) | -0.012 | | | |
| | (-1.210) | | | |
| Trademark Age Dummy | | -0.054*** | | |
| | | (-6.483) | | |
| Log(1+Famous) | | | -0.041*** | |
| | | | (-4.984) | |
| Famous Dummy | | | | -0.040** |
| | | | | (-2.744) |
| Baseline controls | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Observations | 568 | 568 | 568 | 568 |
| R-squared | 0.412 | 0.415 | 0.414 | 0.413 |

Panel B: Trademark strategy

| Variables | Underpricing | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Trademark Diversity | -0.056*** | | |
| | (-3.784) | | |
| Log(1+Exploration) | | -0.014** | |
| | | (-2.326) | |
| Log(1+Exploitation) | | | -0.012 |
| | | | (-1.774) |
| Baseline controls | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes |
| Observations | 570 | 4,321 | 4,321 |
| R-squared | 0.417 | 0.429 | 0.429 |

Panel C: Trademark type

| Variables | Underpricing | |
|---|---|---|
| | (1) | (2) |
| Log(1+ Product Trademark) | -0.016** | |
| | (-2.417) | |
| Log(1+ Marketing Trademark) | | -0.034* |
| | | (-2.181) |
| Baseline controls | Yes | Yes |
| Industry fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 4,321 | 4,321 |
| R-squared | 0.430 | 0.430 |

## Table 7 The impact of information asymmetry

This table examines whether the negative effect of trademarks on underpricing is stronger when firm information asymmetry is higher. The dependent variable is IPO underpricing. The independent variable is *Trademark Dummy* in Panel A and *Log(1+Trademark)* in Panel B, respectively. We use firm age, firm sales, R&D expense, and return residual volatility from Fama French three-factor model as information asymmetry proxies. We conduct subsample tests base on whether the value of the four proxies is above the sample median or not. All baseline controls from Column (2) in Table 3 are included in the regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in the Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level.

Panel A: Explanatory variable: *Trademark dummy*

| | Underpricing | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Young | Mature | Small | Large | High R&D | Low R&D | High volatility | Low volatility |
| Trademark Dummy | -0.051** | -0.005 | -0.046* | 0.003 | -0.046*** | 0.004 | -0.042** | -0.001 |
| | (-3.013) | (-0.766) | (-1.882) | (0.357) | (-5.004) | (0.445) | (-3.045) | (-0.107) |
| Differences | -0.046*** | | -0.049* | | -0.050*** | | -0.041** | |
| Chi-Square | 8.29 | | 3.01 | | 18.19 | | 5.27 | |
| P-value | 0.004 | | 0.083 | | 0.000 | | 0.022 | |
| Baseline controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,213 | 2,108 | 2,211 | 2,110 | 2,315 | 2,006 | 2,105 | 2,216 |
| R-squared | 0.444 | 0.373 | 0.450 | 0.402 | 0.474 | 0.330 | 0.459 | 0.273 |

Panel B: Explanatory variable: *Log(1+Trademark)*

| | Underpricing | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Young | Mature | Small | Large | High R&D | Low R&D | High volatility | Low volatility |
| Log (1+Trademark) | -0.038** | -0.007 | -0.028* | -0.006 | -0.029** | -0.004 | -0.026*** | -0.005 |
| | (-2.475) | (-1.601) | (-2.086) | (-1.094) | (-2.933) | (-0.815) | (-3.524) | (-1.304) |
| Differences | -0.031** | | -0.022* | | -0.025*** | | -0.021*** | |
| Chi-Square | 5.62 | | 3.01 | | 7.09 | | 6.92 | |
| P-value | 0.018 | | 0.083 | | 0.008 | | 0.009 | |
| Baseline controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,213 | 2,108 | 2,211 | 2,110 | 2,315 | 2,006 | 2,105 | 2,216 |
| R-squared | 0.444 | 0.373 | 0.450 | 0.402 | 0.474 | 0.330 | 0.459 | 0.273 |

## Table 8 The impact of product market competition

This table examines whether the negative effect of trademarks on underpricing is stronger when product market competition is higher. The dependent variable is IPO underpricing. The *HHI* is calculated based on the public firm's sales in the same industry (3-digit SIC) as the IPO firm. We conduct subsample tests base on the *HHI*. The dependent variable is *Trademark Dummy* in Columns (1) and (2) and *Log(1+Trademark)* in Columns (3) and (4), respectively. All baseline controls from Column (2) in Table 3 are included in the regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in the Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level.

| | Underpricing | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| | High Competition | Low Competition | High Competition | Low Competition |
| Trademark Dummy | -0.054*** | 0.001 | | |
| | (-8.180) | (0.085) | | |
| Log(1+Trademark) | | | -0.038*** | -0.005 |
| | | | (-5.852) | (-0.753) |
| Differences | -0.055*** | | -0.033*** | |
| Chi-Square | 9.28 | | 17.88 | |
| P-value | 0.002 | | 0.000 | |
| Baseline controls | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Observations | 2,227 | 2,094 | 2,227 | 2,094 |
| R-squared | 0.429 | 0.445 | 0.429 | 0.445 |

## Table 9 Evidence from other IPO outcomes

This table examines the relation between pre-IPO trademark and other IPO outcomes, including the probability of IPO withdrawal, IPO delisting, and post-IPO long-run performance. Panel A report the results between pre-IPO trademark and the likelihood of IPO withdrawn. The dependent variable is a dummy variable indicating whether an IPO is withdrawn. The independent variable is *Trademark Dummy* in Column (1) and *Log(1+Trademark)* in Column (2), respectively. Panel B reports the results between pre-IPO trademark and the likelihood of IPO firm delisting. The dependent variable is a dummy variable indicating whether an IPO delisted within a five-year period after IPO. The independent variable is *Trademark Dummy* in Column (1) and *Log(1+Trademark)* in Column (2), respectively. Panel C reports the results between trademark and IPO long-run operating performance. The dependent variable is the 3-year monthly market-adjusted returns (*Return_Adj*) for Columns (1) and (2) and the ROA in the third fical year after IPO in Columns (3) and (4), respectively. The independent variable is *Trademark Dummy* in Columns (1) and (2) and *Log(1+Trademark)* in columns (3) and (4), respectively. For Panel A, we include both successful and failed IPOs and control for *Underwriter*, *Tech Dummy*, *Internet Dummy*, *Nasdaq Dummy*, *Market Return*, and *Log (1+Hot)*. For Panel B, and Panel C, all baseline controls from Column (2) in Table 3 are included in the regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in the Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: IPO withdrawal

| VARIABLES | IPO Withdraw | |
|---|---|---|
| | (1) | (2) |
| Trademark Dummy | -0.111*** | |
| | (-7.910) | |
| Log(1+Trademark) | | -0.057*** |
| | | (-6.777) |
| | | |
| Industry fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 10,230 | 10,230 |
| R-squared | 0.171 | 0.170 |

Panel B: IPO delisting within 5 years after IPO

| VARIABLES | IPO Delisting | |
|---|---|---|
| | (1) | (2) |
| Trademark Dummy | -0.199*** | |
| | (-18.594) | |
| Log(1+Trademark) | | -0.102*** |
| | | (-13.571) |
| | | |
| Baseline controls | Yes | Yes |
| Industry fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Sample Period | 1980-2011 | 1980-2011 |
| Observations | 4,001 | 4,001 |
| R-squared | 0.098 | 0.095 |

Panel C: Post-IPO long-run performance

| VARIABLES | Return_Adj | | ROA | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Trademark Dummy | 0.281*** | | 0.026** | |
| | (6.802) | | (2.896) | |
| Log(1+Trademark) | | 0.159*** | | 0.019*** |
| | | (7.005) | | (3.611) |
| | | | | |
| Baseline controls | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Observations | 3,680 | 3,680 | 3,110 | 3,110 |
| R-squared | 0.068 | 0.068 | 0.292 | 0.292 |

## Table 10 Propensity Score Matching

This table reports results from propensity score matching. For each IPO firm with at least one trademark (treatment sample) at the IPO date, we find a matched firm (control sample) with zero trademarks. We adopt a logit regression model to calculate the propensity score and use the nearest score matching method. The matching variables include *VC*, *Underwriter*, and *Log (Asset)*. Panel A reports the balancing property after the match and Panel B reports the OLS regression results using the matched sample. In Panel B, the dependent variable is *Trademark Dummy* and *Log(1+Trademark)* in Column (1) and Column (2), respectively. All baseline controls from Column (2) in Table 3 are included in the regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in Appendix Table A2. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level.

Panel A: Balancing property

| VARIABLES | Treatment Sample | Control Sample | Difference | t-value |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VC | 0.534 | 0.552 | -0.018 | -0.60 |
| Underwriter | 0.444 | 0.450 | -0.006 | -0.18 |
| Log (Asset) | 4.020 | 3.976 | 0.044 | 0.50 |

Panel B: The OLS regression using the matched sample

| VARIABLES | Underpricing | |
|---|---|---|
| | (1) | (2) |
| Trademark dummy | -0.030*** | |
| | (-3.288) | |
| Log(1+Trademark) | | -0.023*** |
| | | (-3.354) |
| Baseline Controls | Yes | Yes |
| Industry fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 1,096 | 1,096 |
| R-squared | 0.431 | 0.432 |

## Table 11 Remove the confounding effect of patenting and advertising activities

This table reports the regression results that remove the confounding effect of patents. The dependent variable is IPO underpricing, the independent variable is log(1+patent) in columns (1), trademark dummy and log(1+patent) in column (2), log(1+trademark) and log(1+patent) in (3) and log(1+trademark) in column (4). The regressions are based on the full sample in column (1) to (3) and based on the subsample that firms have filed at least one trademark but never filed any patent before IPO in columns (4). All baseline controls from Column (2) in Table 3 are included in the regressions, whose coefficients are not reported for brevity. Detailed variable definitions are provided in the Appendix. Robust t-statistics, adjusted for industry-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at 1% and 99% level. A constant is always included in regressions although not reported.

| VARIABLES | IPO underpricing | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Trademark dummy | | -0.022** | | |
| | | (-2.344) | | |
| Log(1+trademark) | | | -0.011** | -0.063*** |
| | | | (-2.411) | (-5.150) |
| Log(1+patent) | 0.009 | 0.009 | 0.009 | |
| | (0.897) | (0.916) | (0.929) | |
| Baseline controls | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Sample period | 1980-2006 | 1980-2006 | 1980-2006 | 1980-2016 |
| Observations | 3,740 | 3,740 | 3,740 | 443 |
| R-squared | 0.448 | 0.448 | 0.448 | 0.387 |