# Trademarks in Entrepreneurial Finance

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**Abstract**

We analyze the role of trademarks in entrepreneurial finance, hypothesizing that trademarks play two important roles: a protective role, leading to better product market performance; and an informational role, signaling higher firm quality to investors. We develop testable hypotheses relating the trademarks held by private firms to characteristics of venture capital (VC) investment in them, their probability of successful exit, IPO and secondary market valuations, institutional investor IPO participation, post-IPO operating performance, and post-IPO information asymmetry. We test these hypotheses using a large and unique dataset of trademarks held by VC-backed private firms and present causal evidence supporting them.

Keywords: Trademarks; Initial Public Offerings (IPOs); Private Firm Exit; Innovation

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# 1 Introduction

Trademarks are an important determinant of the economic value created by firms. A trademark is a word, symbol, or other signifier used to distinguish a good or service produced by one firm from the goods or services of other firms (see, e.g., Landes and Posner (1987)). Firms use trademarks to differentiate their products from those of other firms, reduce search costs for consumers, and to generate consumer loyalty through advertising, all of which may affect their product market performance and therefore their financial performance. However, despite the importance of trademarks for the economic activities of firms, there is a relatively little evidence on the role played by trademarks in entrepreneurial finance: i.e., in the financing, performance, and valuation of young firms at various stages in their life.[1]

The objective of this paper is to fill the above gap in the literature. We develop testable hypotheses regarding the relation between the number of trademarks held by firms and various aspects of VC investments in them; their probability of successful private-firm exit (IPOs or acquisitions); the IPO and secondary market valuations of the subsample of these firms that go public; institutional investor participation in these IPOs; their post-IPO operating performance; and the post-IPO information asymmetry faced by these firms. We test these hypotheses using a large and unique dataset of 55,977 trademarks registered by VC-backed firms over the years 1985-2015 and data on VC investment in these firms, data on their exit decisions, and on the IPO valuations and post-IPO operating performance of the subsample of these firms that go public.

We hypothesize that trademarks play two economically important roles in entrepreneurial finance. First, as we discussed earlier, trademarks allow start-up firms to differentiate their products from those of other firms, reduce search costs for consumers, and to generate consumer loyalty through advertising, all of which may affect their product market performance and therefore their financial performance. From now onwards we will refer to this role of trademarks as a "protective role." Second, trademarks may convey credible (but possibly noisy) information about future firm performance (and therefore intrinsic firm value) to private investors such as VCs and public equity market investors, in a setting of asymmetric information between firm insiders and outside investors. Different from patents (which

[1] One exception is Block, De Vries, Schumann, and Sandner (2014), who investigate the relation between the number of trademark applications by VC-backed start-up firms and the valuations of these start-up firms by VCs, which we discuss in the next section.

primarily capture technological innovation), a trademark may signal the intention and ability of a firm to launch and continue a new product line (associated with that trademark). Therefore, assuming that it is costly to acquire and maintain trademarks, a firm's trademark portfolio may serve as a credible signal of firm value to both private investors and public equity market investors (such as investors in the IPO market or potential acquirers of the firm). From now onwards, we will refer to this role of trademarks as their "informational role."

The above broad hypotheses about the protective and the informational role of trademarks generate two sets of testable predictions about entrepreneurial firms. The first set of testable predictions deal with private firms. First, given that firms with a larger number of trademarks are likely to have better future financial performance and this information is inferred by private equity investors (such as VCs) by observing the number of trademarks registered by these firms, we would expect, *ceteris paribus*, the amount of VC investment in private firms to be positively related to the number of trademarks held by these firms.[2] Second, one of the reasons for staging suggested by the literature on VC staging is to take advantage of the real option to discontinue further investment in a firm as they accumulate more information about the firm over time. Since trademarks may convey information to VCs about future firm performance (and therefore about intrinsic firm value), this motivation of VC staging suggests that the number of stages of VC investment will be negatively related to the number of trademarks registered by the firm. Third, we expect private firms with a larger number of trademarks to have a greater probability of a successful exit either through an IPO or an acquisition. This may arise partially due to the protective role of trademarks (which enable firms with a larger number of trademarks to have better future financial performance) and partially due to the informational role of trademarks (since a larger number of trademarks may convey information about better future firm performance to both potential IPO market investors and to potential acquirers).

The second set of testable predictions deal with the subset of VC-backed entrepreneurial firms that eventually go public. First, we expect VC-backed private firms with a larger

[2] It is well-known among practitioners (such as entrepreneurs and VCs) that intellectual property is an important determinant of VC investment in a private firm: see, e.g., the news article, "Do Venture Capitalists Care about Intellectual Property?", *Forbes Magazine*, August 11, 2015. However, the focus in the academic literature has only been on the relation between the size of the patent portfolio of a start-up firm and the signal it sends to investors: see, e.g, Hsu and Ziedonis (2008).

number of trademarks to receive higher IPO and immediate secondary market valuations. This may arise partially due to the protective role of trademarks (which enable firms with a larger number of trademarks to have better future financial performance) and partially due to the information role of trademarks (since a larger number of trademarks may convey information about better future financial performance to potential IPO market investors). Second, we expect the IPOs of such firms to have greater institutional investor participation. As in the case of the previous prediction, this prediction also arises partially from the protective role of trademarks and partially from their informational role. Third, we expect VC-backed firms going public with a larger number of trademarks to have better post-IPO operating performance. Since this prediction is generated only through the protective role of trademarks (and not through their informational role), our empirical test of this prediction may be viewed as a direct test of the protective role of trademarks. Finally, we expect VC-backed firms going public with a larger number of trademarks to be faced with a smaller extent of information asymmetry in the post-IPO equity market. Since this prediction is generated primarily through the informational role of trademarks, our empirical test of this fourth prediction may be viewed as a direct test of the informational role of trademarks.

To test the above hypotheses, we retrieve round-level information on VC investment in entrepreneurial firms which receive their first and last round of investment between 1990 and 2010. We use the Thomson One Global New Issues database and Mergers and Acquisitions database to obtain IPO and acquisition data, respectively. We obtain trademark data from the United States Patent and Trademark Office (USPTO) website. We use standard datasets to construct our innovation measure (used as control variables): the NBER Patent Citation database, the Harvard dataverse, and the USPTO website. Our final sample consists of 13,989 VC-backed private firms. Our second set of empirical tests focus on the subset of VC-backed firms that went public: our final sample for this analysis consists of 1048 firms that went public over the period 1990 to 2015. We obtain accounting data from the Compustat database and stock price data from the Center for Research in Security Prices (CRSP) database. We acquire underwriter reputation data from Prof. Jay Ritter's website. We obtain information on institutional investor shareholdings from the Thomson Reuters Institutional Holdings (13 F) database. Finally, we obtain analyst coverage data from the I/B/E/S database.

We now discuss the results of our empirical analysis. We first summarize the results of our first set of empirical tests, which analyze the impact of the number of trademarks held by private firms on the investment behavior of VCs in these firms and on the exit decisions of these firms. First, private firms with a larger number of trademarks are associated with a larger amount of total VC investment. This result is statistically and economically significant. A one standard deviation increase in our trademark measure is associated with a 1.1 percent (0.27 million dollars) increase in total funding for the median firm in our sample. Second, private firms with a larger number of trademarks are associated with a lower extent of staging by VCs. A one standard deviation increase in our trademark measure is associated with a 3.2 percent increase in the fraction of investment in round 1 for the median firm. Consistent with this, the total number of rounds of VC investment also declines with the number of trademarks held by the firm at the time of initial VC investment. Lastly, private firms with a larger number of trademarks have a greater chance of a successful exit. A one standard deviation increase in our trademark measure is associated with a 2.2 percentage point increase in the probability of successful exit, where successful exit is defined as exit either through an IPO or acquisition. Overall, the results of our first set of empirical tests provide support for both the protective and the informational role of trademarks. It is also important to note that, in all our empirical tests, we control for the number of patents held by a firm and the number of citations to these patents.[3]

We now summarize the results of our second set of empirical tests which analyze the relation between the number of trademarks held by a firm at the time of IPO and its IPO characteristics and post-IPO operating performance. First, VC-backed firms with a larger number of trademarks have higher IPO and immediate secondary market valuations. A one standard deviation increase in our trademark measure is associated with 78.9 percent and 38.6 percent increases in IPO and immediate secondary market valuations, respectively (as measured by their Tobin's Q), for the median firm in our sample. Second, VC-backed firms going public with a larger number of trademarks are associated with greater institutional investor participation at the IPO. A one standard deviation increase in our trademark measure is associated with a 1.8 percent increase in the number of institutional investors investing in

[3]Some papers in the literature have argued that there is a correlation between trademark activity and various measures of innovation (Mendonça, Pereira, and Godinho (2004); Faurel, Li, Shanthikumar, and Teoh (2016)). We control for patents in all our analyses to demonstrate that our results on the relation between the number of trademarks and various outcome variables in entrepreneurial finance are independent of the effects of patents on these variables.

the median firm. Third, VC-backed firms going public with a larger number of trademarks at IPO are associated with better post-IPO operating performance. In terms of economic magnitude, a one standard deviation increase in our trademark measure is associated with an increase of 0.034 in *OIBDA* in the first year after IPO. This increase is substantial given that the median value of *OIBDA* in the first year after IPO is -0.06. Fourth, such firms face a smaller extent of information asymmetry in the equity market, as measured by analyst coverage and dispersion in analyst forecasts. A one standard deviation increase in our trademark measure is associated with a 21.1 percent decrease in the mean dispersion in analyst forecasts and a 7.6 percent increase in the analyst coverage for a median firm. Overall, the results of our second set of empirical tests provide further support for the protective and informational roles of trademarks. In particular, the results of our empirical analysis of the post-IPO operating performance of the subset of VC-backed firms going public provide direct support for the protective role of trademarks, while the results of our empirical analysis of the post-IPO information asymmetry facing such firms provide direct support for the informational role of trademarks.

It may be argued that the relations we have established so far using our baseline analysis between a larger number of trademarks and various private firm and IPO characteristics are endogenous. For example, a higher quality private firm may apply and receive a larger number of trademarks, so that the relations that we documented above between the number of trademarks and the probability of successful private firm exit may be the result of higher firm quality rather than the number of trademarks held by the firm. We, therefore, use an instrumental variable (IV) analysis to establish causality.[4] We instrument for the number of trademarks registered by a firm using a measure of trademark examiner leniency. Trademark applications are randomly assigned to examining attorneys (examiners), who have significant discretion in the examining process. This exogenous variation in examiner leniency may affect the outcome of applications which are on the margin of acceptance or rejection. We, therefore, instrument for the number of granted trademarks using the average examiner leniency calculated across all the trademark applications (accepted or rejected) made by a

[4]We also address endogeneity using a propensity score matching analysis, which is presented in an Internet appendix to this paper. Our propensity score matching results are consistent with those of our baseline OLS regression analyses. We demonstrate that firms with a larger number of trademarks have higher IPO and immediate secondary market valuations, have greater institutional investor participation, have better post-IPO operating performance, and face a smaller extent of information asymmetry in the equity market.

firm in a two-year period. The results of our IV analysis establish that VC-backed firms with a larger number of trademarks have a greater chance of a successful exit. Further, we show that firms with a larger number of trademarks have higher IPO and immediate secondary market valuations, have greater institutional investor participation, have better post-IPO operating performance, and face a smaller extent of information asymmetry in the post-IPO equity market.

The rest of the paper is organized as follows. Section 2 discusses the relation of our paper to the existing literature. Section 3 outlines the underlying theory and develops testable hypotheses for our empirical tests. Section 4 describes our data and sample selection procedures. Section 5 presents our baseline regression analyses and results. Section 6 presents our instrumental variable analyses and results. Section 7 concludes. The results of our propensity-score matching analyses are presented in an Internet Appendix (not to be published).

## 2 Relation to the Existing Literature and Contribution

Our paper is related to several strands in the literature. The strand in the literature closest to our paper is the one that analyses how intellectual property (such as patents and trademarks) held by private firms affects the investment decisions of VCs in these firms and firm valuation by VCs, the valuation of these firms at IPO, and their post-IPO operating performance. For example, one paper in this literature is Hsu and Ziedonis (2008), who study how patents held by innovative firms affect investments by VCs in these firms; see also Cao and Hsu (2011).[5] Block, De Vries, Schumman, and Sandner (2014) show that the number and breadth of trademarks have inverted U-shaped relationship with financial valuation of start-ups by VCs.[6] Our paper is also related to papers analyzing the relation between patents held by private firms at IPO, their IPO valuation, and their post-IPO performance: see, e.g., Chemmanur, Gupta, and Simonyan (2016), who study the relation between private firms' innovation at IPO and their IPO and secondary market valuation, and their post-IPO operating performance; and Cao, Jiang, and Ritter (2013), who study the relation between

[5]In a contemporaneous related paper, Farre-Mensa, Hegde, and Ljunqvist (2017) use an instrumental variable analysis to show that patent approvals help startups create jobs, grow their sales, attract investment from VCs, and eventually have successful exits.

[6]Zhou, Sandner, Martinelli, and Block (2016) show that patents and trademarks have a direct and complementary effect on VC financing.

the number of patents held by VC-backed firms at IPO and their post-IPO stock returns. Our paper is also closely related to the literature analyzing how firms' going public decisions affect their innovation productivity. Two theoretical models that incorporate the effect of going public on the innovation productivity of a firm are Ferreira, Manso, and Silva (2014) and Spiegel and Tookes (2016). Both models predict that private firms will be more innovative pre-IPO rather than post-IPO, though for reasons somewhat different from each other. Bernstein (2015) empirically analyzes how the innovation productivity of firms changes from before an IPO to after, and shows that going public leads to a decline in the innovation productivity of firms. Another paper that studies the relation between entrepreneurial exit choice and innovation outcomes is Agarwal and Hsu (2014), who find that innovation quality is highest under private ownership and lowest under public ownership, with acquisition intermediate between the two. Barrot (2017) analyzes how the contractual horizon of venture capital funds affects their investments in innovative firms and shows that investment by VC-funds with a longer horizon results in greater growth in these firms' patent portfolios. Ours is, however, the first paper in the literature to analyze the relation between the number of trademarks held by private firms and VC investment patterns (total investment and staging of investment) and the relation between the number of trademarks held by private firms and their probability of successful exit. It is also the first to analyze the relation between the number of trademarks and the IPO characteristics of VC-backed private firms going public (IPO and immediate secondary market valuations, institutional investor participation in the IPO, post-IPO information asymmetry), and also the first to analyze the relation between the number of trademarks held by a private firm at IPO and its post-IPO operating performance. Finally, it is also the first paper to demonstrate a causal relation between the number of trademarks held by a private firm and the above mentioned variables.

Our paper also contributes to several strands in the broader entrepreneurial finance literature. First, we contribute to the literature dealing with investment behavior of VCs in private firms: see, e.g., Gompers (1995), who analyzes how agency costs and information asymmetry affect VC staging, and Tian (2011), who studies how the distance between VC investors and start-up firms affect the staging of VC investments. Second, we contribute to the literature dealing with the exit decisions of private firms: see, e.g., Lerner (1994), who analyzes the going public decisions of venture-backed private firms; Chemmanur, He, and Nandy (2009), who analyze the relation between the product market characteristics of private firms and their going public decisions; and Chemmanur, He, He, and Nandy (2018), who analyze the relation between the product market characteristics of private firms and their exit choice between IPOs, acquisitions, and remaining private. Third, we contribute to the literature relating various characteristics of a private firm at IPO and its IPO characteristics: see, e.g., Chemmanur and Paeglis (2005), who analyze the relation between the top management quality of a firm at IPO and its IPO characteristics.[7] Fourth, we contribute to the literature relating various characteristics of private firms to their IPO and post-IPO operating performance: see, e.g., Jain and Kini (1994) and Loughran and Ritter (1997). Finally, our paper contributes to the literature on entrepreneurship and the determinants of entrepreneurial firm success. There is a significant theoretical literature modeling entrepreneurial firms (see, e.g., Chen, Miao, and Wang (2010)) and the dynamics of entrepreneurship (Wang, Wang, and Yang (2012)). There is also a significant empirical literature in this area: see, e.g., Moskowitz and Vissing-Jorgensen (2002) and Hall and Woodward (2010). Our paper contributes indirectly to this last strand in the literature by showing, for the first time, that an important determinant of entrepreneurial firm success is the portfolio of trademarks held by private firms.

Finally, our paper contributes to the broader literature on trademarks, patents, and other forms of intellectual property.[8] Faurel, Li, Shanthikumar, and Teoh (2016) use a sample of publicly traded (S&P 1500) firms to analyze the relation between CEO incentives and the number of trademarks created by firms. Hsu, Li, Liu, and Wu (2017) demonstrate that companies with large portfolios of trademarks and fast growth in trademarks are likely to be acquirers, while companies with a narrow breadth of trademarks and slow growth in trademarks are likely to be target firms. Exploiting the Federal Trademark Dilution Act (FTDA), Heath and Mace (2016) find that trademark protection is of first-order importance for firm profits. Our paper is also related, though more distantly, to the empirical literature on corporate innovation. One strand in this literature focuses on how various firm characteristics affect innovation in established firms, such as: managerial compensation (Ederer and Manso (2013)); private equity or venture capital involvement (e.g., Lerner, Sorensen, and Stromberg (2011), Tian and Wang (2014), Chemmanur, Loutskina, and Tian (2014)); anti-takeover provisions (e.g., Atanassov (2013), Chemmanur and Tian (2018), Sapra, Sub-

[7]See Ritter and Welch (2002) for an excellent review of the theoretical and empirical literature on IPOs.
[8]For an excellent review of the economics of intellectual property, see Besen and Raskind (1991).

ramnian, and Subramanian (2014)); institutional ownership (e.g., Aghion, Van Reenen, and Zingales (2013)); CEO overconfidence and CEO characteristics (e.g., Hirshleifer, Low, and Teoh (2012), Barker and Mueller (2002)); conglomerate structure (e.g., Seru (2014)); and shareholder litigation (Lin, Liu, and Manso (2017)). Another strand in this literature focuses on the valuation of innovation by the stock market: see, e.g., Kogan, Papanikolaou, Seru, and Stoffman (2017) and Cohen, Diether, and Malloy (2013).

# 3 Theory and Hypothesis Development

We hypothesize that trademarks play two economically important roles relevant for the financing of private firms and their exit decisions. First, they may help to distinguish the products of a firm from those sold by other firms: see, e.g., Economides (1988).[9] In other words, trademarks give the owner legal protection by granting the exclusive right to use them to identify goods or services, or to license its use to another entity in return for payment (see, e.g., Mendonça, Pereira, and Godinho (2004)). Further, trademarks may help to enhance the product market performance of the firms which own trademarks in a variety of other ways. For example, in a setting where sellers have better information about the unobservable features of the product than consumers themselves, trademarks accomplish two tasks (see, Economides (1988)): (i) They facilitate and enhance consumer decisions by identifying the unobservable features of the trademarked product; (ii) they create incentives for firms to produce products of desirable quality even when quality is not observable before purchase. They may also allow for "perception advertising" whereby a mental image may be added to the quality and various other features of a trademarked product. This allows the firm to generate consumer loyalty to trademarks, thus deterring entry by competitors. In summary, trademarks may enhance the value of the firm's products (and its product market performance) in many different ways. This, in turn, implies that trademarks may also help to enhance the future financial performance of a firm. We refer to this direct effect of trademarks on the future financial performance of a private firm as the "protective" role

[9] Economides (1988) points out: "The producer (or distributor) is given a legal monopoly on the use of these trademarked symbols and names in connection with the attached commodity and is extensively protected against infringement. Similarly, under certain circumstances, the law allows a word or symbol used to identify a business entity as a trade name to be registered and used exclusively."

of trademarks.[10]

The second important economic role that trademarks may play in the life of young firms is of conveying information about their intrinsic value and future financial performance to investors. In other words, they may act as a credible (but possibly noisy) signal to private investors such as VCs and public equity market investors, in a setting of asymmetric information between firm insiders and outside investors. Different from patents (which primarily capture technological innovation), a trademark may signal the intention and ability of a firm to launch and continue a new product line (associated with that trademark).[11] Therefore, assuming that it is costly to acquire and maintain trademarks, a firm's trademark portfolio may serve as a credible signal of intrinsic firm value to both private investors and public equity market investors (such as investors in the IPO market or potential acquirers of the firm), over and above any information conveyed by the firm's patent portfolio.[12] We will refer to this role of trademarks as their "informational" role.[13]

Of course, the number of trademarks registered by a firm may not be a fully revealing signal of firm value. In other words, if the cost of acquiring a trademark is not higher than the valuation and other benefits obtained by the firm from registering it, the equilibrium in the financial market (either in the private or in the public equity market) may be a

[10]On a related note, trademarks can also be viewed as reducing the search costs of consumers in the product market: see, e.g., Landes and Posner (1987). In this paper we refer to the direct effect of trademarks on improving the product and therefore the financial market performance of a firm through various different channels as arising from the protective role of trademarks.

[11]As Mendonça, Pereira, and Godinho (2004) note, the common expectation in trademark regimes is that a registered trademark is used, otherwise it may be canceled and may be assigned to another company after a period of grace. Its maintenance by economic agents can thus be seen as indicating the exercise of regular business activities; an unused trademark is implicitly regarded by Intellectual Property Rights (IPR) law as a barrier to economic activity.

[12]See Long (2002) for a theoretical model demonstrating how a firm's patent portfolio may serve as a signal of intrinsic firm value to outside observers. See also Chemmanur and Yan (2009), who show that product market advertising is able to serve as a signal of firm quality (intrinsic value) to both the product and financial markets. From an economic point of view, trademarks have some similarity to advertising, since the value of trademarking a product goes up as the true quality of the product is higher (given that the probability of repeat purchases is greater for higher quality products). While it is easy to develop a similar game-theoretical model of how a firm's trademark portfolio may convey information to outside investors about firm value, we will refrain from doing so here due to space limitations.

[13]The informational and protective roles of trademarks may interact with each other. Thus, the number of trademarks held by a firm may convey information to investors not only about the firm's intention to launch and maintain a certain number of product lines, but also about its future strength in the product market (arising from the partial monopoly power associated with these trademarks).

partial pooling equilibrium (rather than a fully separating equilibrium). Thus, firms having a wide range of intrinsic values may pool together partially by acquiring the same number of trademarks (i.e., within a certain band of characteristics, higher intrinsic valued firms may be unable to fully distinguish themselves credibly from lower intrinsic valued firms using only their trademarks). Nevertheless, even in the case of a partial pooling equilibrium, investors may be able obtain some information, albeit noisy, about the future performance of a firm from observing the number of trademarks registered by it.[14]

In the following, we develop testable hypotheses relating the number of trademarks registered by a private firm to the investment behavior of VCs in the firm; to its probability of a successful exit (IPOs or acquisitions); to its IPO and secondary market valuations; and to its post-IPO operating performance. We will rely on either the protective role or the informational role of trademarks (or both) that we discussed above to develop testable hypotheses relating the number of trademarks registered by a firm to the above variables.

## 3.1 The Relation between Trademarks, the Investment Behavior of VCs, and Successful Private Firm Exit

### *3.1.1 The Relation between Trademarks and the Size of Venture Capital Investments in the Firm*

We argued earlier that trademarks have a protective role and an informational role. First, VCs would expect firms with a larger number of trademarks to perform better in the product market (through the protective role of trademarks that we discussed earlier). Second, the number of trademarks may also convey favorable information about the firm's intrinsic value to VCs (the information role we discussed earlier). For both of these reasons, we expect the total amount of investment made by VCs in a private firm to be increasing in the number of trademarks held by the firm at the time of investment (**H1**).

[14] Of course, if it is completely costless for firms to acquire trademarks (even in the absence of any intention to establish a product line corresponding to that trademark), the equilibrium in the financial market will be a fully pooling equilibrium, so that no information will be conveyed to investors by the size of a firm's trademark portfolio. However, the reputation cost to a firm's founders of applying for and obtaining frivolous trademarks which they have no intention of maintaining through actual use is likely to be substantial. Therefore, even if the upfront legal and administrative costs of obtaining trademarks are small, the equilibrium in the financial market is unlikely to be a fully pooling equilibrium.

### 3.1.2 The Relation between Trademarks and Venture Capital Staging

We now turn to the relation between the number of trademarks registered by a firm and the extent of staging of VC investment (i.e, the number of rounds the total VC investment in the firm is split up into). It has been argued that VC staging and monitoring are substitutes (see, e.g., Tian (2011)). This is because, given that investing in a larger number of rounds is associated with greater contracting and other costs, VCs are likely to invest in higher quality firms (requiring less monitoring) using a smaller number of stages (investment rounds). Given that a larger number of trademarks registered to a firm may signal higher firm quality (higher intrinsic value and better future operating performance), this means that the number of stages of VC investment will be negatively related to the number of trademarks registered by a firm.[15] Given the smaller number of financing rounds that a VC's total investment is split up into, we also expect firms holding a larger number of trademarks to be associated with a larger fraction of the total VC investment to be made in the firm in the very first VC investment round itself (**H2**).

### 3.1.3 Trademarks as a Predictor of Successful Private Firm Exit

We argued earlier that trademarks have a protective role, so that trademarks may be associated with better product market and financial performance. If the above effects of the protective role of trademarks on firm performance is considerable, then it may significantly enhance the future earnings of trademark-holders. Further, IPO market investors and the potential acquirers of private firms may become convinced of this, since the number of trademarks registered by a private firm may convey a favorable signal about firm quality to these outsiders: i.e., trademarks may play an informational role as well, as discussed earlier. For both of these reasons, we expect firms with a larger number of trademarks to have a greater probability of a successful exit either through an IPO or an acquisition (**H3**).

[15]The number of trademarks registered by a firm may also be negatively related to the number of stages of VC investment through the learning channel (with or without information asymmetry). For example, Gompers (1995) argues that VCs generate a "real option" to discontinue further investment in the firm as they accumulate more information over time (about firm quality) by funneling their investment over multiple stages. Chemmanur and Chen (2014) develop a model of a firm's equilibrium choice between VCs and angel investors where a VC invests in an entrepreneurial firm under asymmetric information, and leaves the firm after initial financing rounds if he finds that his early round investments are not very productive. In either of the above settings, since the number of trademarks convey favorable information about firm quality, a larger number of trademarks will be associated with a smaller number of VC financing rounds.

## 3.2 Trademarks as a Signal to IPO Market Investors

### *3.2.1 The Relation between Trademarks and Firm Valuation in the IPO and Secondary Market*

We now turn to the relation between the number of trademarks held by a firm and its IPO and secondary market valuations. Given that, as we have argued above, trademarks have a protective role, we expect firms with a larger number of trademarks to have better future operating performance. In a setting of symmetric information, the secondary market value of a firm will be equal to the present value of its future cash flows, so that, in such a setting, the number of trademarks will be positively related to the firm's secondary market valuation. Further, given that a larger number of trademarks may convey more favorable information to equity market investors (through the informational role of trademarks discussed earlier), we expect the above positive relationship between the immediate post-IPO secondary market valuation and the number of trademarks registered by the firm to hold even in a setting of asymmetric information between firm insiders and outsiders (**H4**).

Next, we discuss the relationship between the number of trademarks held by a firm and its valuation at the IPO offer price. This relationship depends on the process of setting the offer price in IPOs. While there is no consensus in the theoretical and empirical IPO literature on precisely how the IPO offer price is set, this price-setting process can be broadly thought of as the following. During the book-building and road-show process, the lead underwriter conveys information about the IPO firm to institutions (this, in turn, may affect their valuation of the firm). The lead underwriter may also extract information from institutional investors about their valuation of the IPO firm and their demand for the firm's share. Toward the end of the book-building and road-show process, the lead underwriter uses the above information to establish the highest uniform price at which it can sell all the shares offered in the IPO (i.e., the market-clearing price, which is also the underwriter's expectation of the first day secondary market closing price), and then applies a "discount" to the market clearing price, thus establishing the actual IPO offer price (typically on the evening before the IPO). One possible explanation for such a discount is to compensate institutional investors for their cost of producing information about the IPO firm (see, e.g., Chemmanur (1993)).[16] Since

[16]There are a number of alternative theories in the IPO literature that may explain this IPO discount: see, e.g., Benveniste and Spindt (1989) for another theory based on bookbuilding. Regardless of the underlying

trademarks may serve as a signal of intrinsic firm value to institutional investors and reduce their cost of information production, we expect this discount to be smaller for firms which have registered a larger number of trademarks. Consequently, we expect firms with a larger number of trademarks to have a higher IPO market valuations (**H5**).

*3.2.2 The Relation between Trademarks and Institutional Investor Participation*

As we posited earlier, trademarks may play a protective role, allowing firms to perform better post-IPO. Further, as discussed earlier, the number of trademarks held by a firm may play an informational role by conveying its potential for better future operating performance (and therefore higher intrinsic value) to institutional investors in the IPO market. Consequently, assuming that institutional investors choose to participate to a greater extent in the IPOs of better firms (as measured by expected future performance), we would expect the IPOs of firms with a larger number of trademarks to be associated with greater participation by institutional investors (**H6**).

## 3.3 Direct Tests of the Protective and the Informational Role of Trademarks

*3.3.1 A Direct Test of the Protective Role of Trademarks*

We argued earlier that trademarks may play a protective role, thereby allowing the firm to perform better in the product market, thus enhancing the future earnings of trademark-holders. Therefore, we expect firms with a larger number of trademarks to have better post-IPO operating performance (**H7**). Given that the relation between the number of trademarks held by a firm and its post-IPO operating performance is related only to the protective role of trademarks (i.e., unrelated to the informational role of trademarks) our test of the above hypothesis may be viewed as a direct test of the protective role of trademarks.

*3.3.2 A Direct test of the Informational Role of Trademarks*

We posited earlier that trademarks are positive (but possibly noisy) signals of intrinsic firm value to investors: i.e., they may play an informational role. If this is the case, both

theory that may explain the IPO discount, the prediction that the IPO valuation of a firm will be increasing in the number of trademarks registered by the firm at the time of IPO will hold as long as the discount to the market clearing price set by IPO underwriters is not assumed to be increasing in the number of trademarks held by the IPO firm.

institutional and retail investors in the IPO market may have more accurate information about firms which possess a larger number of trademarks. Therefore, we expect firms with a larger number of trademarks to face a smaller extent of information asymmetry in the post-IPO equity market (**H8**). Given that the relationship between the number of trademarks and the information asymmetry facing the firm after the IPO is likely to be related only to the informational role of trademarks (i.e., unrelated to the protective role of trademarks), our test of the above hypothesis may be viewed as a direct test of the informational role of trademarks.

# 4 Data and Sample Selection

## 4.1 Sample Selection

We obtain data on VC-backed private firms in the U.S. from Thomson One VentureXpert. We retrieve round-level information on VC investments in entrepreneurial firms that received their first and last round of investment between January 1, 1990 and December 31, 2010. We use the Thomson One Global New Issues database and Thomson One Mergers and Acquisitions database to obtain information on IPOs and acquisitions, respectively. We exclude firms that received their first round of VC investment after their IPO, which leaves us with 24,508 distinct entrepreneurial firms in the U.S. We identify lead VC investor for each entrepreneurial firm following Nahata (2008) and use VentureXpert to extract their respective age and fund size. After dropping observations with missing data on lead VC or other relevant firm characteristics, we are left with a sample of 13,989 VC-backed private firms. We obtain the trademark data from the USPTO website. We use the 2006 edition of the National Bureau of Economic Research (NBER) Patent Citation database (see Hall, Jaffe, and Trajtenberg (2001) for details) for information on patent applications and grants as well as their respective forward citations. We augment this dataset with patent data from the Harvard Patent Network Dataverse, which contains patent and citation information till 2010. Finally, we use the USPTO website to obtain patent data from 2011 to 2015. Panel A and Panel B of Table 1 provide summary statistics for our sample of VC-backed private firms.

In the second half of our paper, we shift our focus toward VC-backed firms that eventually went public. Out of the 24,508 entrepreneurial firms, 2,106 firms had achieved successful exits via IPOs. Accounting data comes from the Compustat and stock price data comes from the Center for Research in Security Prices (CRSP). We obtain underwriter reputation data from Professor Jay Ritter's website (https://site.warrington.ufl.edu/ritter/ipo-data/). After excluding missing data and merging the above datasets, we are left with a sample of 1,048 public firms. We obtain institutional shareholders' information from the Thomson Reuters Institutional Holdings (13 F) database. Analyst coverage data comes from the Institutional Brokers' Estimate System (I/B/E/S) database. Panel C of Table 1 provides summary statistics for our sample of VC-backed firms that eventually went public.

## 4.2 Measures of Trademarks

We obtain the list of all the trademark applications available in the USPTO database till 2015. We only consider trademarks that are successfully registered. As per the USPTO website, a trademark life-cycle begins with a firm selecting a mark and filing it with the USPTO to be registered as a trademark. Upon filing the application, the USPTO checks for the minimum filing requirements and assigns a serial number to the application provided the application meets the filing criteria. After the assignment, the USPTO appoints an examining attorney to review the application. The examining attorney performs a complete examination of the application to determine whether the mark is eligible for registration. If the examining attorney believes that the mark meets statutory registration criteria, he will approve the application for publication. Otherwise, he will issue an office action explaining grounds for rejection or suggest minor corrections if required.[17] Once the trademark is deemed registrable by the examining attorney, it is published for opposition in the Official Gazette. If no official objection is raised within the next 30 days, the USPTO proceeds with registration.

We match the trademark dataset with the VentureXpert dataset using the firm name as identifier and adopt a similar matching technique to the one used in the NBER Patent Project. We assume that a VC-backed firm does not have any trademark if we cannot match its name against the trademark dataset. For a particular firm, we count the number of trademarks it has registered from five years prior to receiving the first round of VC investment to the year of concern, which in our study is either the year of receiving the first round of VC investment or the year of exit. We do this to maintain the same event

[17] See Graham, Hancock, Marco, and Myers (2013) for more details.

time window for all firms. Following Faurel, Li, Shanthikumar, and Teoh (2016), we use the registration year of trademarks for constructing our measure of trademarks. We use a log measure (*Ln(1 + No. of Trademarks)*) to capture the value of trademarks for a particular firm. We take the natural logarithm because the distribution of trademarks is skewed. We add one to the actual values to avoid losing observations with zero trademarks. Panel A of Table 1 reports summary statistics for the trademark measure at the time of the first round of VC investment. Panel C of Table 1 reports summary statistics of trademarks for public firms at time of IPO.

## 4.3 Measures of Innovation

We control for a firm's innovation output and innovation quality in our regressions. We obtain patent and citation data from the NBER Patent Citation Database, the Harvard Patent Network Dataverse, and the USPTO website. The USPTO website publishes weekly patent grant data in the XML format. We collate all the weekly XML files from 2011 to 2015 and parse them to collect patent and citation information. We match the combined patent dataset with the VentureXpert dataset using the same matching technique that we use to match the trademark dataset with the VentureXpert data.

Patent data is subject to two types of truncation problems. First, patents are included in the dataset only after they are granted and on average there is a two-year lag between a patent application and the eventual grant. Therefore, we observe a smaller number of patents which are granted towards the last few years of our sample period. We address this problem by dividing each patent for each firm-year by the mean number of patents for all firms for that year in the same 3-digit technology class as the patent (Seru (2014)). As suggested in Hall, Jaffe, and Trajtenberg (2001), we consider the application year of a patent for constructing our measures of innovation. The second type of truncation problem pertains to citation count. For a given patent, we count the number of forward citations it has received till 2015. Patents tend to receive citations over a long period of time but not many citations during the initial years. As a result, the citation count of later year patents in our sample will be downward biased. For example, patents filed in 2013 are likely to have a smaller number of forward citations than the ones filed in 2005. We adjust this truncation bias by scaling citations of a given patent by the total number of citations received by all the patents filed in the same 3-digit technology class and year (Seru (2014)). Thus we obtain class-adjusted measure of patents and citations, adjusted for trend in innovation activity in a particular technology class as specified by the USPTO.

We construct two measures of innovation. The first measure, *Ln(1+No. of Patents)*, is the natural logarithm of one plus the total number of class-adjusted patents for a particular firm from five years prior to receiving the first round of VC investment to the year of concern, which in our study is either the year of receiving the first round of VC investment or the year of exit. The second measure, *Ln(1+No. of Citations)*, is the natural logarithm of one plus the total number of class-adjusted forward citations received by all the patents used in constructing the patent measure. We take the natural logarithm because the distributions of patents and citations are skewed. We add one to the actual values to avoid losing observations with zero patents and citations. Panel A of Table 1 reports the summary statistics for class-adjusted patents and citations at the time of first round of VC investment. Panel C of Table 1 reports the summary statistics of class-adjusted patents and citations for public firms in the year of IPO.

## 4.4 Summary Statistics

Table 1 reports the summary statistics for VC-backed private firms.[18] Panel A shows that the median firm in our sample receives almost half of the total VC funding (48 percent) in the first round and typically receives two rounds of VC investments. The median firm in our sample typically does not have trademarks or patents at the time of receiving the first round of VC investment. Further, the median firm typically has two VC investors investing in the first round.

In Panel B, we present the summary statistics of the eventual exits of VC-backed private firms. Out of 24,508 private firms in our sample, 7,283 (29.7 percent) had a successful exit via acquisition, 2,106 (8.6 percent) had a successful exit via IPO, and the rest did not have an exit. Panel C reports summary statistics for key IPO characteristics of venture-backed firms that eventually went public. The median values of the three valuation measures, *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* are 0.38, 0.88, and 1.08, respectively. We find that the median public firm typically has trademarks and patents in the year of IPO. The median firm has a negative *ROA* of -0.19 in the fiscal year prior to the IPO and a *Tobin's Q* of 0.92.

[18] Note that all the variables are winsorised at 1 percent and 99 percent.

# 5 Baseline Empirical Analyses and Results

## 5.1 The Effect of Trademarks on the Pattern of Investment by VCs

In this section, we study the relation between trademarks and VC investment patterns (i.e., the size and staging of VC investments), which correspond to our hypotheses **H1** and **H2**, respectively. We therefore estimate the following model:

$$Var_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \quad (1)$$

where $i$ indexes firm and $t$ indexes year. To study the relation between VC investment size and trademarks, we use two measures of VC investment as dependent variables in the above model. The first measure is *Ln(Investment in Round 1)*, defined as the natural logarithm of the total VC investments in the first round in a private firm. The second measure is *Ln(Total Investment)*, defined as the natural logarithm of the total VC investments across all rounds in a firm. We take the natural logarithm of investments in order to reduce skewness. To study the relation between the number of trademarks and staging of investments by VCs, we use two measures for the staging of VC investments as dependent variables. The first measure of staging is *Fraction of Investment in Round 1*, defined as the VC investment in the first round divided by the total VC investment across all rounds in a private firm. The second measure of staging is *No. of Rounds by VCs*, defined as the total number of VC investment rounds in a firm. Our explanatory variable of interest is *Ln(1+No. of Trademarks)*. $X$ represents a vector of controls and fixed effects, which are described below.

We use either class-adjusted patents (*Ln(1+No. Patents)*) or citations (*Ln(1+No. Citations)*) to control for the effect of firm-innovation on VC investment size or staging. We control for the age of a private firm (*Ln(1+Firm Age)*), the number of VC investors in the first round (*Syndicate Size*), the age of the lead VC (*Ln(1+VC Age)*), and the fund size of the lead VC (*Ln(VC Fund Size)*). We include fixed effects for industry, year, state of firm headquarters, and the lead VC in our regressions to account for heterogeneity due to these factors. We cluster standard errors at the lead VC level since residuals may be correlated across observations backed by the same lead VC.

We present our results of the above tests in Table 2. In Columns (1) and (2) of Panel A, we use the VC investment size in the first round (*Ln(Investment Round 1)*) as dependent variables. We find that the coefficients of trademarks in these regressions are positive and significant at the 1 percent level. In Columns (3) and (4) of Panel A, we use the total VC investment size across all rounds (*Ln(Total Investment)*) as dependent variables. We find that the coefficients of trademarks are positive and significant in Column (4) but not in Column(3). Our results are also economically significant. A one standard deviation increase in our trademark measure is associated with a $0.18 million increase in the first round of VC investments for the median firm in our sample. Also, a one standard deviation increase in our trademark measure is associated with a 1.1 percent ($0.27 million) increase in the total VC investments across all rounds for the median firm in our sample. These results suggest that private firms with a larger number of registered trademarks are associated with greater VC investment, which supports our hypothesis **H1**.

In Columns (1) and (2) of Panel B, we use the fraction of VC investment in the first round (*Fraction of Investment in Round 1*) as dependent variables. We find that the coefficients of trademarks are positive and statistically significant at the 1 percent level. In Columns (3) and (4) of Panel B, we use the number of rounds of VC investment (*No. of Rounds by VCs*) as the dependent variable and find that coefficients of trademarks are negative and statistically significant at the 1 percent level. In terms of economic magnitude, a one standard deviation increase in our trademark measure is associated with a 0.015 increase in the fraction of VC investment in the first round. For the median firm, this is equivalent to a 3.2 percent increase in the first-round investment. Also, one standard deviation increase in our trademark measure is associated with a decrease of 0.1 rounds in terms of the staging of VC investment. These results suggest that private firms with a larger number of registered trademarks are associated with a lower extent of staging of investments by VCs, which supports our hypothesis **H2**.

## 5.2 The Effect of Trademarks on Successful Private Firm Exit

We study the relation between the number of trademarks and successful exits of VC-backed private firms, corresponding to our hypothesis **H3**, by estimating the following probit model:

$$\mathit{Pr(Exit)}_{it} = \alpha_0 + \alpha_1 \mathit{Ln(1 + No.\ of\ Trademarks)}_{it} + X_{it} + \epsilon_{it}, \tag{2}$$

where $i$ denotes the firm and $t$ denotes the year of a firm's exit. We use three measures of successful exit (*Exit*) as dependent variables. Existing literature considers both the IPO and acquisition as a successful exit (see, e.g., Gompers and Lerner (2000) and Nahata (2008)). Therefore, our first measure is a dummy variable *IPO and M&A*, which is equal to 1 if a venture-backed private firm went public or was acquired within five years of the last round of VC investment and 0 otherwise. Our second measure is a dummy variable *IPO only*, which is equal to 1 if a venture-backed private firm went public within five years of the last round of VC investment and 0 otherwise. Our third measure is a dummy variable *M&A only*, which is equal to 1 if a venture-backed private firm was acquired within five years of the last round of VC investment and 0 otherwise. For public (acquired) firms, trademarks and patents are measured from 5 years prior to the first round of VC investment to the year of IPO (acquisition). For all other firms, trademarks and patents are measured from five years prior to the first round of VC investment to five years after the last round of VC investment, which we consider as the year of write-off (see, e.g., Tian (2012)). $X$ represents a vector of controls and fixed effects, which are described below.

In the above regressions, we control for firm innovation using either class-adjusted patents or citations since it may affect the probability of a firm's successful exit. Following the existing literature (see, e.g., Tian (2011)), we include a set of other control variables in our regressions such as the age of a private firm, total VC investments, the age of the lead VC, fund size of the lead VC, the total number of rounds of VC investments, and the average number of VC investors per round.[19] We include in the regressions dummy variables for industry, year of last round of VC investment, firm-headquarters state, and lead VC, respectively, and cluster standard errors at the lead VC level.

We present our results of the above regressions in Table 3. In Columns (1) and (2), we use IPO and acquisition dummy as the dependent variable. We find that the coefficients of

[19] We control for the age of a private firm (*Ln(1+Firm Age)*) as firms at the mature stage of life-cycle are expected to have a lower extent of information asymmetry. We control for the total VC investment across all rounds (*Ln(Total Investment)*) as it is an indicator of VCs' perception of the firm. We control for the age of the lead VC (*Ln(1+VC Age)*) as experienced VCs are better in selecting high quality firms to invest. We also control for the fund size of the lead VC (*Ln(VC Fund Size*) as it determines the total investment and may affect the likelihood of a successful exit. We control for the number of rounds of investment by VCs (*No. of Rounds by VCs*) as it is a staging variable and may indicate the quality of the private firm as perceived by VCs. Finally, we control for the mean number of VC investors per round (*Average No. of VCs per Round*), a proxy for the syndication, as syndication may help source better value creating service for firms.

trademarks are positive and significant at the 1 percent level. In Columns (3) and (4), we use the IPO dummy as the dependent variable. We find that, here also, the coefficients of trademarks are positive and significant (at the 5 percent and 1 percent level, respectively). Finally, in Columns (5) and (6), we use the acquisition dummy and find that the coefficients of trademarks are positive and significant at the 1 percent level. Our results are also economically significant: a one standard deviation increase in our trademark measure is associated with a 2.2 percentage point, 0.35 percentage point, and 1.8 percentage point increase in the probability of a successful exit by either IPO and M&A, IPO only, and M&A only, respectively. These results suggest that firms with a larger number of trademarks are associated with a greater chance of successful exit, which supports our hypothesis **H3**.

## 5.3 The Effect of Trademarks on IPO and Secondary Market Valuations

We now study the relation between the number of trademarks and the IPO and immediate secondary market valuations of VC-backed forms going public, corresponding to our hypotheses **H5** and **H4**, respectively. We estimate the following model:

$$Valuation_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \tag{3}$$

where $i$ denotes the firm and $t$ denotes the year of IPO. We construct our valuation measures using Tobin's Q, which is the ratio of market value of assets over the book value of assets.[20] We measure IPO market valuation using the IPO offer price. We measure secondary market valuation using two different measures: using first trading day closing price as the share price and using the share price at the end of the first post-IPO fiscal quarter. We construct industry-adjusted Tobin's Q ratios for all the three measures, *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation(FQ)*, by subtracting contemporaneous two-digit SIC code industry-median Q ratios from the above proxies.[21] $X$ represents a vector of controls and fixed effects, which are described below.

[20]The market value of assets is equal to the book value of assets minus the book value of equity plus the product of number of shares outstanding and share price.

[21]The book value of assets and the book value of equity for both IPO firms and their industry peers are taken from the first available post-IPO quarter on Compustat. The number of shares outstanding for IPO firms is measured as of the first trading day. The number of shares outstanding and the share price for industry peers are measured as of the end of the first available post-IPO quarter on Compustat.

The explanatory variable of interest in our regressions is the trademark measure. We control for innovation using either class-adjusted patents or citations as they may affect IPO valuations. Following the existing literature, our other control variables include underwriter reputation, firm size, total IPO proceeds, and previous year operating performance. We include fixed effects for industry, year, and state of firm headquarters. We cluster standard errors at the two-digit SIC code industry level since residuals will be correlated across observations in the same industry.

We present our results of the above tests in Table 4. In Columns (1) and (2), the dependent variable is IPO valuation. We find that the coefficients of trademarks are positive and significant (at the 1 percent level). In Columns (3) and (4), the dependent variable is secondary market valuation computed using first day closing price. The coefficients of trademarks in these regressions are positive and significant at the 10 percent and 5 percent level, respectively. Finally, in Columns (5) and (6), our dependent variable is the secondary market valuation computed using first post-IPO fiscal quarter share price. Here also, the coefficients of trademarks are positive and significant at the 5 percent and 1 percent level, respectively. Our results are also economically significant: a one standard deviation increase in our trademark measure is associated with an increase of 0.30, 0.34, and 0.53 for *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* respectively. These increases are equivalent to 78.9 percent, 38.6 percent, and 49.1 percent increase in *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* for the median firm, respectively. In sum, our empirical results presented in this subsection show that firms with a larger number of trademarks are associated with larger IPO and immediate secondary market valuations, which supports our hypotheses **H5** and **H4**, respectively.

## 5.4 The Effect of Trademarks on the Participation of Institutional Investors in a Firm's IPO

We now study the relation between the number of trademarks held by firms and participation of institutional investor in their IPOs (corresponding to our hypothesis **H6**) by estimating the following model:

$$MP_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \tag{4}$$

where $i$ denotes the firm and $t$ denotes the year of IPO. We use the natural logarithm of one plus the total number of institutional investors holding shares in a firm (*Ln(1+No. of Institutional Investors)*) as the dependent variable. The explanatory variable of interest in our regressions is our trademark measure. $X$ represents a vector of controls and fixed effects, which are described below. We control for firm innovation using either class-adjusted patents or citations since they may affect the participation of institutional investors. Following the existing literature (see, e.g., Bajo, Chemmanur, Simonyan, and Tehranian (2016)), our other control variables include underwriter reputation, total IPO proceeds, firm age, underpricing, operating performance, and Tobin's Q.[22] We include fixed effects for industry, year, and firm-headquarter state in our regressions and cluster standard errors at the two-digit SIC code industry level.

We present our empirical results of the above regressions in Table 5. In Columns (1) and (2), we find that the coefficients of trademarks are significant at the 10 percent level. Our results are also economically significant: a one standard deviation increase in our trademark measure is associated with a 1.8 percent increase in the number of institutional investors investing in the firm. These results suggest that firms with a larger number of trademarks are associated with greater institutional investor participation, which supports our hypothesis **H6**.

## 5.5 The Effect of Trademarks on Post-IPO Operating Performance

In this subsection, we study the relation between the number of trademarks and the post-IPO operating performance of VC-backed public firms (corresponding to our hypothesis **H7**), which can be viewed as a direct test of the protective role of trademarks. We estimate the following model:

$$OP_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}. \tag{5}$$

[22] We control for underwriter reputation (*Ln(Underwriter Reputation)*) as the involvement of more reputable underwriters will attract market players in the IPO. We also control for firm size (*Ln(Assets)*), proceeds from the IPO (*Ln(IPO Proceeds)*), age of firms (*Ln(1+Firm Age)*), and *underpricing*. Aggarwal, Krigman, and Womack (2002) show that managers use underpricing to improve demand for the stock. Finally, we control for pre-IPO industry adjusted operating performance measure (*ROA*) and industry adjusted *Tobin's Q* since firms that are better preforming and have received higher valuations are likely to have greater participation by institutional investors.

In the above model, the dependent variable $OP_{\mathrm{it}}$ is the operating performance measure, and $i$ denotes the firm and $t$ denotes the year of IPO. We measure post-IPO operating performance using *OIBDA*, the industry-adjusted ratio of operating income before depreciation plus interest income (Compustat item 13 and 62, respectively) to the book value of total assets (item 6): see, e.g., Jain and Kini (1994) and Loughran and Ritter (1997). *OIBDA* is adjusted for industry performance by subtracting contemporaneous industry (two-digit SIC code) median. This measure is constructed for the year of IPO (i.e., year 0) as well as the following three years post-IPO (i.e., year 1, 2, and 3). The explanatory variable of interest in our regressions is our trademark measure. $X$ represents a vector of controls and fixed effects, which are described below. We control for firm innovation using either class-adjusted patents or citations since they may have an impact on operating performance. Our other control variables include underwriter reputation (*Ln(Underwriter Reputation)*), firm size (*Ln(Assets)*), firm age (*Ln(1+Firm Age)*), pre-IPO industry adjusted operating performance (*ROA*), and industry adjusted *Tobins' Q*. We include fixed effects for industry, year, and state of firm headquarters in our regressions and cluster standard errors at the two-digit SIC code industry level.

We present our results of the above tests in Table 6. We find that the coefficients of trademarks are positive but insignificant in the IPO year. However, in each of the three years after IPO, we find that the coefficients of trademarks are positive and significant (in Columns (3) to (8)). In terms of economic magnitude, a one standard deviation increase in our trademark measure is associated with an increase of 0.034 in *OIBDA* in the first year after IPO. This increase is substantial, given that the median value of *OIBDA* in the first year after IPO is -0.06. In sum, our results presented in this section suggest that firms with a larger number of trademarks are associated with better post-IPO operating performance, which supports our hypothesis **H7**.

## 5.6 The Effect of Trademarks on the Information Asymmetry Facing the firm in the IPO Market

We study the relation between the number of trademarks and the information asymmetry facing the firm in the equity market (corresponding to our hypothesis **H8**). This may be viewed a direct test of the informational role of trademarks. We therefore estimate the following model:

$$Asymmetry_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \tag{6}$$

where $i$ denotes the firm and $t$ denotes the year of IPO. We use three measures of information asymmetry as dependent variables in the above model. The first measure is the mean squared error of analyst forecasts (*Forecast Error*). We measure mean squared error as the absolute difference between average earnings forecast and the actual earnings per share divided by the price per share at the time of the forecast. Our second measure of information asymmetry is the standard deviation of analyst forecasts (*Dispersion*). Our third measure of information asymmetry is the total number of analysts covering the IPO firm (*No. of Analysts*). The explanatory variable of interest in our regressions is our trademark measure. $X$ represents a vector of controls and fixed effects, which are described below. We control for innovation using either class-adjusted patents or citations as they may affect the information asymmetry facing a firm. We control for underwriter reputation (*Ln(Underwriter Reputation)*), firm size (*Ln(Assets)*), firm age (*Ln(1+Firm Age)*), and industry adjusted *Tobin's Q*. We include fixed effects for industry, year, and state of firm headquarters in our regressions and cluster standard errors by the two-digit SIC code industry level.

We present our results of the above tests in Table 7. In Columns (1) and (2), we use the analyst forecast error as the dependent variable and find that the coefficients of trademarks are negative but insignificant. In Columns (3) and (4), we use the analyst forecast dispersion as the dependent variable and find that the coefficients of trademarks are negative and significant at the 10 percent level. In Columns (5) and (6), we use the number of analysts covering the firm as the dependent variable and find that the coefficients of trademarks are positive and significant at the 10 percent and 5 percent level, respectively. These results suggest that firms with a larger number of trademarks are associated with a smaller extent of information asymmetry in the equity market, which supports our hypothesis **H8**. Our results are also economically significant. For example, a one standard deviation increase in our trademark measure is associated with a reduction of 0.09 in *Dispersion*, which is equivalent to a 21.1 percent reduction in the average *Dispersion*. Also, a one standard deviation increase in our trademark measure is associated with an increase of 0.23 in number of analysts covering a firm, which is equivalent to a 7.6 percent increase in the average *No.*

*of Analysts.*

# 6 Instrumental Variable Analysis

It may be argued that the relations we have established so far using our baseline analyses between a larger number of trademarks and various private firm and IPO characteristics are the result of omitted variables: for example, a higher quality private firm may apply for and receive a larger number of trademarks, so that the relations that we documented above between the number of trademarks and the probability of successful private firm exit may be the result of higher firm quality rather than the number of trademarks held by the firm. In other words, the unobservable firm quality may be driving our results. To address this concern, we conduct an IV analysis making use of the random assignment of trademark applications to trademark examining attorneys and the exogenous source of variation in attorney leniency in approving trademark applications. Our quasi-experimental approach builds on similar applications in the literature.[23] We describe the construction of our instrument in detail in the next subsection.

## 6.1 Instrumental Variable: Average Examiner Leniency

We use average examiner leniency as an instrument for the number of trademarks granted to a firm. Examining attorneys (examiners) are randomly assigned to review applications in the order in which the applications are received by the USPTO and to determine whether registration of the application is permissible by federal law. A generic or merely descriptive mark will be rejected and so will be a mark that can create a "likelihood of confusion" with an existing trademark.[24] Therefore, a degree of subjectivity and examiner discretion is involved in the examination process of trademark applications, and we exploit this discretion in our IV analysis. We realize that applying for trademarks is an endogenous choice of a firm. There may be some firms that are able to apply for trademarks but choose not to do so. Therefore, in our quasi-experimental set-up, we only focus on firms that have applied for trademarks

[23]Maestas, Mullen, and Strand (2013) exploit the variation in allowance rate of disability insurance examiners to show the disincentive effect of benefits. Sampat and Williams (2015), Farre-Mensa, Hedge, and Ljungqvist (2017), Gaule (2015), and Melero, Palomeras, and Wehrheim (2017) use patent examiner leniency as instrument for patents in their research.

[24]See Graham, Hancock, Marco, and Myers (2013) for a detailed study on the life-cycle of trademark application.

(with varying degrees of success). The success rate of an application will largely depend on the quality of the application: in general, a high quality trademark application will be more likely to get approved compared to a low-quality application. However, our argument is that the success of applications on the margin of approval and rejection will depend, at least partially, on the leniency of the examiner assigned to review the application. An application assigned to a more lenient examiner will be more likely to be approved compared to an application of similar quality assigned to a less lenient examiner. We therefore compute a time-varying measure of the leniency of each individual examiner. Specifically, the approval rate of examiner $j$ assigned to review trademark application $i$ in year $t$ is defined as follows:

$$\textit{Individual Examiner Leniency}_{ijt} = \frac{\textit{Grants}_{jt} - \textit{Grant}_i}{\textit{Applications}_{jt} - 1}. \tag{7}$$

where $\textit{Grants}_{jt}$ and $\textit{Applications}_{jt}$ are the numbers of trademark granted and applications reviewed, respectively, by examiner $j$ in the same application year as application $i$.[25] $\textit{Grant}_i$ denotes the outcome of an application $i$ and takes the value 1 if the application is approved and 0 otherwise . Intuitively, the empirical setup follows prior research on examiners that leaves out the application itself while computing the examiner approval rate.[26] Since we are interested in obtaining an instrument for the number of trademarks granted to a firm, we average examiner leniency across applications. We consider all the trademark applications filed by a firm in the two-year window prior to its successful exit (IPO or acquisition). We choose the two-year window to calculate average examiner leniency because a longer time window may wash out the heterogeneity in leniency across examiners. We then compute the average examiner leniency for a firm over the two-year window as the instrument for the number of trademarks registered by the firm. Specifically, we compute our instrument, i.e., the average examiner leniency ($\textit{Avg Leniency}_{it}$) for a firm $i$ in year $t$, as follows:

$$\textit{Avg Leniency}_{it} = \frac{1}{n_i} \sum_j \textit{Individual Examiner Leniency}_{ijt}, \tag{8}$$

[25] Note that we are using a time-varying measure of examiner leniency. Therefore, the variation in the approvals of trademark applications will be driven by both within-examiner variation and cross-examiner variation.

[26] See, e.g., Maestas, Mullen, and Strand (2013), Gaule (2015), Melero, Palomeras, and Wehrheim (2017).

where $j$ indexes trademark examiner and $n_i$ is the total number of trademark applications filed by firm $i$ in the two year window.

The first and second-stage regressions of our IV analysis are as follows :

$$Ln(1{+}No.\ of\ Trademarks)_{it} = \alpha_1 Avg\ Leniency_{it} + \alpha_2 Applications_{it} + \alpha_3 X_{it} + \epsilon_{it}. \tag{9}$$

$$Outcome_{it} = \beta_1 Ln(1{+}No.\ of\ \hat{}Trademarks)_{it} + \beta_2 Applications_{it} + \beta_3 X_{it} + \epsilon_{it}. \tag{10}$$

In the first-stage regression (equation (9)), we regress $Ln(1{+}No.\ of\ Trademarks)_{it}$ on the instrument ($Avg\ Leniency_{it}$), i.e., the average examiner leniency computed for firm $i$. $Ln(1{+}No.\ of\ Trademarks)_{it}$ is defined as the natural logarithm of one plus the total number of trademarks granted to a firm in the two-year window. $Applications_{it}$ is the number of trademark applications filed in the two-year window and $X_{it}$ is a vector of controls and fixed effects used in prior tests. Equation (10) presents the second stage of our IV (2SLS) regressions, where we regress different outcome variables ($Outcome_{it}$) on the predicted value of the natural logarithm of one plus the total number of trademarks, computed from the first stage.

### *6.1.1 Instrument Relevance*

We make use of a subsample of 6,358,500 trademark applications filed till 2015, for which we have examiner information available. We only consider examiners who have examined more than 10 applications in a year. Figure 1 shows the distribution of examiners' yearly approval rates (as defined in equation (7)), from which we observe significant variation in the examiners' approval rates: the median examiner yearly approval rate is 55.97 percent and the interquartile range is 9.52 percent.

We find that the average examiner leniency for a firm is highly correlated with the number of trademarks registered by the firm in the two-year window, as reported in all the first-stage regression results of our instrumental variable analysis (i.e., Column (1) in Tables 8 to 12). In all these first-stage regressions, we find that the coefficients of the instrument are positive and highly significant at the 1 percent level. The F-statistics in these first-stage regressions exceed the critical value of 10 (Stock and Yogo (2002)). These results suggest that our instrument satisfies the required relevance condition for a strong instrument.

### *6.1.2 Exclusion Restriction*

In order to satisfy the exclusion restriction, our instrumental variable should affect the outcome variables (including VC-backed private firm and IPO characteristics) only through its relation with the endogenous variable, i.e., the number of trademarks registered by a firm in the two-year window prior to the successful exit. Angrist and Pischke (2008) argue that for an instrument to satisfy the exclusion restriction, the following two conditions must hold: First, the instrument should be randomly assigned, i.e., independent of potential outcomes, conditional on covariates; second, the instrument should have no effect on outcomes other than through the first-stage channel. In our analyses, the first condition is satisfied since the trademarks applications are randomly assigned to examiners, irrespective of the quality of an application. Further, applicants do not know the identity of trademark examiners when the USPTO assigns applications to trademark examiners. Applicants become aware of the identity of examiners only *ex-post* when either their application is approved or they receive an office action explaining the grounds for refusal and/or possible options for responding to the refusal. Since a firm does not know the identity of its application examiner *ex-ante*, they cannot take actions which may affect the outcome variables in the period between the assignment of an application to an examiner and the outcome of the application. In summary, our instrument satisfies the exclusion restriction as well.

## 6.2 Empirical Results of Instrumental Variable Analysis

### *6.2.1 Instrumental Variable Analysis of Successful Private Firm Exit*

Here, we run a two-stage probit regression model (as shown in equations (9) and (10)) and use measures of successful exits as the dependent variable in the second stage. We include the same controls and dummy variables as in our corresponding baseline probit regressions. We also include an additional control, i.e., the number of applications ($Applications_{it}$) in both stages, to control for the fact that a firm with more applications may be likely to have more registered trademarks.

We report other results of these regressions in Table 8. In Column (1), we report the first-stage regression result of our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 22.74 and the adjusted R-squared is 25.7 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. We report the second-stage regression results in Columns (2) to (7). In Columns (2) and (3), the dependent variable is a dummy variable for IPOs and acquisitions (*IPO and M&A*). We find that the coefficients of the trademark measure are positive and significant at the 1 percent level. In Columns (4) and (5), the dependent variable is a dummy variable for IPOs (*IPO only*). The coefficients of the trademark measure are positive but insignificant. Finally, in Columns (6) and (7), the dependent variable is a dummy variable for acquisitions (*M&A only*). We find that the coefficients of the trademark measure are positive and significant at the 1 percent level. In sum, our IV analysis results show that the positive relation between trademarks on the likelihood of successful exits of VC-backed private firms is causal. This supports our hypothesis **H3**.

#### *6.2.2 Instrumental Variable Analysis of IPO and Secondary Market Valuation*

We report our IV regression results of the effects of trademarks on IPO and secondary market valuations in Table 9. In Column (1), we present the first-stage regression results of our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 46.24 and the adjusted R-squared is 21.8 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. We present the second-stage regression results in the Columns (2)-(7). In Columns (2) and (3), we use a firm's IPO valuation (*IPO Valuation*) as the dependent variable and find that the coefficients of our trademark measure are positive but insignificant. In Columns (4) and (5), we use a firm's secondary market valuation computed using first day closing price (*Secondary Valuation (FD)*) as the dependent variable and find that the coefficients of our trademark measure are positive and significant at the 1 percent level. Finally, in Columns (6) and (7), we use the secondary market valuation computed using first post-IPO fiscal quarter price (*Secondary Valuation (FQ)*) as the dependent variable and find that the coefficients of our trademark measure are positive and significant. In sum, our IV analysis results show that trademarks have a positive and causal effect on firm valuation, which supports our hypothesis **H4**.

#### *6.2.3 Instrumental Variable Analysis of the Participation of Institutional Investors in a Firm's IPO*

We report our IV regression results of the effects of trademarks on the participation of institutional investors in a firm's IPO in Table 10. In Column (1), we show the first-stage regression results of our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 91.08 and the adjusted R-squared is 19.9 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. We present the second-stage regression results in Columns (2) and (3), in which the dependent variable is the natural logarithm of one plus the number of institutional investors investing in the IPO firm (*Ln(1+No. of Institutional Investors)*). We find that the coefficients of our trademark measure are positive and significant at the 10 percent level. In sum, our IV analysis results confirm that trademarks have a positive and causal effect on institutional investor participation in an IPO firm, which supports our hypothesis **H6**.

#### *6.2.4 Instrumental Variable Analysis of Post-IPO Operating Performance*

We report our IV regression results of the effect of trademarks on a firm's post-IPO operating performance in Table 11. In Column (1), we report the first-stage regression results of our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 93.28 and the adjusted R-squared is 28.6 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. We report the second-stage results in Columns (2)-(9). Columns (2) and (3) use *OIBDA* in the IPO year as the dependent variable. Columns (4)-(9) use *OIBDA* in the years 1, 2, and 3 after IPO as dependent variables. We find that the coefficients of our trademark measure are positive and significant at the 10 percent level only for the case of post-IPO operating performance in year 3 (Columns (8) and (9)). Broadly, our IV analysis results suggest that trademarks play a protective role, i.e., firms with a larger number of trademarks have better post-IPO operating performance, which supports our hypothesis **H7**.

#### *6.2.5 Instrumental Variable Analysis of Information Asymmetry Facing the Firm in the Post-IPO Market*

We report our IV regression results of the effect of trademarks on the information asymmetry facing the firm in the post-IPO market in Table 12. In Column (1), we present the first-stage regression results of our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant (at the 1 percent level). The first-stage F-statistic is 162.42 and the adjusted R-squared is 30.9 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. We report the second-stage regression results in Columns (2)-(7). In Columns (2) and(3), we use the analyst forecast error (*Forecast Error*) as the dependent variable and find that the coefficients of our trademark measure are negative and significant at the 5 percent level. As for regressions using the other two measures of information asymmetry (*Dispersion* and *No. of Analysts*) as dependent variables, our results are in the right direction but insignificant. Broadly, our results suggest that trademarks play an informational role, i.e., firms with larger number of trademarks face a lower extent of information asymmetry in the equity market, which supports our hypothesis **H8**.

# 7 Conclusion

In this paper, we analyze the role of trademarks in the financing, valuation, and performance of start-up firms, for the first time in the literature. We conjecture that trademarks may play two economically important roles in entrepreneurial finance: first, granting start-up firms some monopoly power in the product market (a protective role) leading them to perform better in the future; and second, signaling better future financial performance and higher intrinsic value to private and public equity investors such as venture capitalists (VCs) and those in the IPO market (an informational role). We develop testable hypotheses regarding the relation between the number of trademarks held by a firm and various aspects of VC investment in it; its probability of successful exit; its IPO and secondary market valuation; institutional investor participation in its IPO; its post-IPO operating performance; and its post-IPO information asymmetry. We test these hypotheses using a large and unique dataset of trademarks held by VC-backed firms and data on VC investment in these firms, on their exit decisions, and on the IPO characteristics (of those firms going public). We find that the number of trademarks held by an entrepreneurial firm is associated with a greater VC investment amount spread over a smaller number of financing rounds; a greater probability of successful exit; higher IPO and secondary market valuations; greater institutional investor IPO participation; smaller post-IPO equity market information asymmetry; and better post-IPO operating performance. We establish using an instrumental variable analysis (using trademark application examiner leniency as the instrument) that the above results are causal.

Overall, our results show that the trademark portfolio held by an entrepreneurial firm is an important determinant of the eventual success of the firm. First, we show that the trademarks held by an entrepreneurial firm help it to attract financing on favorable terms, both as a private firm (from VCs) and later on from public equity market investors (by yielding the firm higher IPO valuations). Second, we have shown that the trademarks held by an entrepreneurial firm are an important predictor of its eventual success, both as a private firm (through a higher successful exit probability) and subsequently as a public firm through helping it to generate better post-IPO operating performance. Our empirical analysis also helps to shed some light on two channels through which trademarks help entrepreneurial firms obtain financing on more favorable terms and lead to better financial performance. First, by signaling a higher probability of success (intrinsic value) to private investors like VCs and to public equity market investors (such as institutional investors and potential acquirers). Second, by enabling the firm to perform better in the product market (e.g., through giving it some monopoly power over its products), which, in turn, translates into better financial (operating) performance.

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**Table 1: Summary Statistics for VC-Backed Private Firms and VC-backed IPO firms**

This table reports summary statistics for the sample of VC-backed private firms in the U.S. between 1990 and 2010 as well as the subsample of VC-backed firms that went public. Panel A shows summary statistics for VC-backed private firms at the time of receiving their first round of investment from VCs. *Fraction of Investment in Round 1* is the fraction of VC investments received by a private firm in the first round out of the total VC investments across all rounds. *No. of Rounds by VCs* is the total number of rounds of VC investments received by a private firm. *Ln(Investment in Round 1)* is the natural logarithm of the total VC investments received by a private firm in the first round. *Ln(Total Investment)* is the natural logarithm of the total VC investments across all rounds received by a private firm. All investments are in millions of dollars. In Panel A, *No. of Trademarks* is the total number of trademarks that a firm has registered in the five-year period before the first round of VC investment. In Panel A, *No. of Patents* is the total number of patents filed and eventually granted to a firm in the five-year period before the first round of VC investment. *Total No. of Citations* is the total number of forward citations received by these patents. In Panel C, *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of receiving the first round of VC investment. *Syndicate Size* is the number of VC firms investing in the first round of investment in a firm. *Ln(1 + VC Age)* is the natural logarithm of one plus the number of years from the founding year of the lead VC to the year of first round of lead VC investment at the private firm. *Ln(VC Fund Size)* is the natural logarithm of fund size (in millions of dollars) of the lead VC at the time of the first round of VC investment in a private firm. Panel B reports the eventual exit status of the firms. We classify a sample firm as *Acquired* if it was acquired by another firm within five years of receiving its last round of VC investment. A sample firm is classified as *Went Public* if it went public within five years of receiving its last round of VC investment. All other firms are classified as *No Exit.* The sample in Panel C consists of VC-backed private firms, between 1990 and 2010, which had IPOs within 5 years of receiving the last round of VC investment. *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* are the industry-adjusted Tobin's Q ratios calculated using the IPO offer price, the first trading day close price, and the price at the end of the first post-IPO fiscal quarter, respectively. Tobin's Q is the ratio of the market value of assets to the book value of the assets, with the market value of assets equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day. The share price we use is the IPO offer price for *IPO Valuation*, the first trading day closing price for *Secondary Valuation (FD)*, or the price at the end of first post-IPO fiscal quarter for *Secondary Valuation (FQ)*. The number of shares outstanding, share price, book value of assets, and book value of equity for industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's two-digit standard-industrial classification code (SIC) code industry peers. *No. of Analysts* is the number of analysts following a firm at the end of the fiscal year of the IPO. *No. of Institutional Investors* is the number of institutional investors holding IPO firm shares at the end of first fiscal quarter after the IPO. In Panel C, *No. of Trademarks* is the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. In Panel C, *No. of Patents* is the total number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Total No. of Citations* is the total number of forward citations received by these patents. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. In Panel C, *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *Prior Market Return* is the return on the CRSP value-weighted index over the 30-day period prior to the IPO.

| Panel A: Summary Statistics at the Time of First Round of Investment in Private Firms | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Std. Dev. | Min | 1st Quartile | Median | 3rd quartile | Max |
| Fraction of Investment in Round 1 | 20,648 | 0.540 | 0.401 | 0.004 | 0.134 | 0.478 | 1 | 1 |
| No. of Rounds by VCs | 24,508 | 3.044 | 2.546 | 1 | 1 | 2 | 4 | 23 |
| Ln(Investment in Round 1) | 20,648 | 0.990 | 1.419 | -2.996 | 0.095 | 1.099 | 1.946 | 4.159 |
| Ln(Total Investment) | 21,740 | 2.173 | 1.645 | -2.590 | 1.154 | 2.355 | 3.385 | 5.298 |
| No. of Trademarks | 24,508 | 0.371 | 1.134 | 0 | 0 | 0 | 0 | 7 |
| No. of Patents | 24,508 | 0.405 | 1.340 | 0 | 0 | 0 | 0 | 9 |
| No. of Citations | 24,508 | 4.092 | 19.670 | 0 | 0 | 0 | 0 | 150 |
| Ln(1 + Firm Age) | 19,218 | 1.057 | 0.980 | 0 | 0 | 0.693 | 1.609 | 4.043 |
| Syndicate Size | 24,508 | 2.035 | 1.323 | 1 | 1 | 2 | 3 | 7 |
| Ln(1 + VC Age) | 17,694 | 2.322 | 0.885 | 0 | 1.792 | 2.485 | 2.944 | 4.220 |
| Ln(VC Fund Size) | 17,911 | 5.671 | 1.696 | 1.386 | 4.508 | 5.746 | 6.970 | 9.329 |

| Panel B: Exit Status of VC-Backed Firms | | |
|---|---|---|
| Status | N | Percent |
| Acquired | 7,283 | 29.717 |
| Went Public | 2,106 | 8.593 |
| No Exit | 15,119 | 61.690 |
| Total | 24,508 | 100 |

| Panel C: Characteristics of VC-Backed IPO Firms | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Std. Dev. | Min | 1st Quartile | Median | 3rd quartile | Max |
| IPO Valuation | 900 | 1.163 | 3.630 | -3.337 | -0.347 | 0.381 | 1.428 | 49.541 |
| Secondary Valuation (FD) | 997 | 2.465 | 5.682 | -3.057 | -0.134 | 0.881 | 2.684 | 65.563 |
| Secondary Valuation (FQ) | 1,048 | 2.979 | 6.604 | -3.021 | -0.035 | 1.082 | 3.277 | 77.628 |
| Number of Analyst | 1,013 | 3.842 | 3.837 | 0 | 1 | 3 | 5 | 29 |
| No. of Institutional Investors | 763 | 32.501 | 22.361 | 2 | 16 | 28 | 44 | 109 |
| No. of Trademarks | 1,048 | 3.088 | 4.777 | 0 | 0 | 1 | 4 | 23 |
| No. of Patents | 1,048 | 6.052 | 10.738 | 0 | 0 | 1 | 7 | 41 |
| Total No. of Citations | 1,048 | 55.420 | 114.206 | 0 | 0 | 0 | 36.5 | 397 |
| Ln(Underwriter Reputation) | 1,048 | 1.919 | 0.555 | 0 | 1.946 | 2.08 | 2.197 | 2.197 |
| Ln(Assets) | 970 | 3.373 | 1.565 | -2.154 | 2.384 | 3.186 | 4.257 | 9.476 |
| Ln(IPO Proceeds) | 981 | 3.995 | 0.877 | -1.386 | 3.497 | 4.025 | 4.511 | 6.864 |
| Ln(1 + Firm Age) | 1,032 | 1.952 | 0.713 | 0 | 1.609 | 1.946 | 2.398 | 4.248 |
| ROA | 953 | -0.415 | 1.075 | -16.954 | -0.571 | -0.192 | 0.027 | 1.532 |
| Tobin’s Q | 997 | 2.465 | 5.682 | -3.057 | -0.134 | 0.881 | 2.684 | 65.563 |

## Table 2: The Relation between Trademarks and the Pattern of Investments by VCs

This table reports the OLS regression results of the effect of trademarks on patterns of investments by VCs. Panel A shows the impact of trademarks on the size of VC investment in the first round and total investment size across all rounds. Panel B shows the impact of trademarks on the staging of investments by VCs. *Fraction of Investment in Round 1* is the fraction of VC investment received by a private firm in the first round out of total VC investments across all rounds. *No. of Rounds by VCs* is the total number of rounds of VC investments received by a private firm. *Ln(Investment in Round 1)* is the natural logarithm of the total VC investments received by a private firm in the first round. *Ln(Total Investment)* is the natural logarithm of the total VC investments across all rounds received by a private firm. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the five-year period before the first round of VC investment. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of receiving the first round of VC investment. *Syndicate Size* is the number of VC firms investing in the first round of investment in a firm. *Ln(1 + VC Age)* is the natural logarithm of one plus the number of years from the founding year of the lead VC to the year of first round of lead VC investment at the private firm. *Ln(VC Fund Size)* is the natural logarithm of fund size of the lead VC at the time of the first round of VC investment in a private firm. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm in the five-year period before the first round of VC investment. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, state of a firm's headquarters fixed effects, and the lead VC fixed effects are included in all regressions. All standard errors are clustered at the lead VC level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: The Effect of Trademarks on the Size of VC Investment

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Variables | Ln(Investment in Round 1) | Ln(Investment in Round 1) | Ln(Total Investment) | Ln(Total Investment) |
| Ln(1 + No. of Trademarks) | 0.133*** | 0.144*** | 0.040 | 0.059** |
| | (0.024) | (0.024) | (0.027) | (0.027) |
| Ln(1 + Firm Age) | 0.173*** | 0.177*** | -0.099*** | -0.092*** |
| | (0.014) | (0.014) | (0.014) | (0.014) |
| Syndicate Size | 0.276*** | 0.277*** | 0.176*** | 0.179*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Ln(1 + VC Age) | -0.070 | -0.073 | -0.091* | -0.096* |
| | (0.056) | (0.056) | (0.055) | (0.055) |
| Ln(VC Fund Size) | 0.268*** | 0.268*** | 0.118*** | 0.118*** |
| | (0.039) | (0.040) | (0.036) | (0.037) |
| Ln(1 + No. of Patents) | 0.201*** | | 0.317*** | |
| | (0.036) | | (0.044) | |
| Ln(1 + No. of Citations) | | 9.862*** | | 10.586*** |
| | | (2.717) | | (3.626) |
| Observations | 11,682 | 11,682 | 12,323 | 12,323 |
| Adjusted R-squared | 0.434 | 0.433 | 0.381 | 0.378 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes |
| Lead VC FE | Yes | Yes | Yes | Yes |

| Panel B: The Effect of Trademarks on the Staging of VC Investment | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Variables | Fraction of Investment in Round 1 | Fraction of Investment in Round 1 | No. of Rounds by VCs | No. of Rounds by VCs |
| Ln(1 + No. of Trademarks) | 0.035*** | 0.030*** | -0.218*** | -0.190*** |
| | (0.008) | (0.008) | (0.044) | (0.043) |
| Ln(1 + Firm Age) | 0.072*** | 0.071*** | -0.319*** | -0.311*** |
| | (0.004) | (0.004) | (0.024) | (0.024) |
| Syndicate Size | 0.008*** | 0.007*** | 0.083*** | 0.087*** |
| | (0.002) | (0.002) | (0.017) | (0.017) |
| Ln(1 + VC Age) | 0.005 | 0.005 | 0.038 | 0.032 |
| | (0.014) | (0.014) | (0.093) | (0.093) |
| Ln(VC Fund Size) | 0.020** | 0.020** | -0.077 | -0.076 |
| | (0.009) | (0.009) | (0.060) | (0.060) |
| Ln(1 + No. of Patents) | -0.061*** | | 0.395*** | |
| | (0.012) | | (0.077) | |
| Ln(1 + No. of Citations) | | -0.674 | | 9.160 |
| | | (1.001) | | (6.995) |
| Observations | 11,682 | 11,682 | 13,329 | 13,329 |
| Adjusted R-squared | 0.332 | 0.330 | 0.272 | 0.271 |
| Industry FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes |
| Lead VC FE | Yes | Yes | Yes | Yes |

**Table 3: The Relation between Trademarks and the Propensity for Successful Exit**

This table reports the probit regression results of successful exits of VC-backed firms on trademarks. In Columns (1) and (2), the dependent variable is a dummy variable equal to one if a private firm went public or was acquired within five years of the last round of VC investment, and zero otherwise. In Columns (3) and (4), the dependent variable is a dummy variable equal to one if a private firm went public within five years of the last round of VC investment, and zero otherwise. In Columns (5) and (6), the dependent variable is a dummy variable equal to one if a private firm was acquired within five years of the last round of VC investment, and zero otherwise. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of exit. The year of exit is the year of IPO or acquisition for a firm, which had a successful exit. Otherwise, the year of exit is set at five years after the last round of VC investment. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of exit. *Ln(Total Investment)* is the natural logarithm of the total VC investments across all rounds received by a private firm. *Ln(1 + VC Age)* is the natural logarithm of one plus the number of years from the founding year of the lead VC to the year of exit. *Ln(VC Fund Size)* is the natural logarithm of fund size of the lead VC in the year of the private firm's exit. *No. of Rounds by VCs* is the total number of rounds of VC investments received by a private firm. *Average No. of VCs per Round* is the ratio of the number of different VC firms investing in a private firm and the number of VC investment rounds in the firm. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of exit. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant and dummy variables for two-digit SIC, year, state of a firm's headquarters, and lead VC are included in all regressions. All standard errors are clustered at the lead VC level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | IPO and M&A | IPO and M&A | IPO only | IPO only | M&A only | M&A only |
| Ln(1 + No. of Trademarks) | 0.050*** | 0.061*** | 0.008** | 0.015*** | 0.042*** | 0.043*** |
| | (0.008) | (0.007) | (0.004) | (0.004) | (0.007) | (0.007) |
| Ln(1 + Firm Age) | -0.012 | -0.009 | 0.013** | 0.014*** | -0.021*** | -0.021*** |
| | (0.008) | (0.008) | (0.005) | (0.005) | (0.007) | (0.007) |
| Ln(Total Investment) | 0.063*** | 0.067*** | 0.042*** | 0.046*** | 0.023*** | 0.024*** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) |
| Ln(1 + VC Age) | -0.052 | -0.062 | -0.023 | -0.028 | -0.025 | -0.026 |
| | (0.041) | (0.041) | (0.019) | (0.020) | (0.029) | (0.029) |
| Ln(VC Fund Size) | -0.579*** | -0.574*** | -0.120*** | -0.121*** | -0.201*** | -0.200*** |
| | (0.033) | (0.033) | (0.008) | (0.008) | (0.017) | (0.017) |
| No. of Rounds by VCs | -0.012*** | -0.011*** | -0.002 | -0.001 | -0.009*** | -0.009*** |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| Average No. of VCs per Round | 0.002 | 0.004 | 0.006** | 0.007** | -0.006 | -0.006 |
| | (0.005) | (0.005) | (0.003) | (0.003) | (0.004) | (0.004) |
| Ln(1 + No. of Patents) | 0.102*** | | 0.051*** | | 0.016* | |
| | (0.010) | | (0.005) | | (0.009) | |
| Ln(1 + No. of Citations) | | 2.694*** | | 0.771*** | | 0.687* |
| | | (0.451) | | (0.196) | | (0.397) |
| Observations | 12,144 | 12,144 | 9,046 | 9,046 | 11,936 | 11,936 |
| Industry dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| State dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| Lead VC dummy | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 4: The Relation between Trademarks and IPO and Secondary Market Valuations

This table reports the OLS regression results of the effect of trademarks on IPO and immediate secondary valuations. *IPO Valuation, Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* are the industry-adjusted Tobin's Q ratios calculated using the IPO offer price, the first trading day close price, and the price at the end of the first post-IPO fiscal quarter, respectively. Tobin's Q is the ratio of the market value of assets to the book value of the assets, with the market value of assets equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day. The share price we use is the IPO offer price for *IPO valuation*, the first trading day closing price for *Secondary Valuation (FD)*, or the price at the end of first post-IPO fiscal quarter for *Secondary Valuation (FQ)*. The number of shares outstanding, share price, book value of assets, and book value of equity for the industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's two-digit standard-industrial classification code (SIC) code industry peers. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | IPO Valuation | IPO Valuation | Secondary Valuation (FD) | Secondary Valuation (FD) | Secondary Valuation (FQ) | Secondary Valuation (FQ) |
| Ln(1 + No. of Trademarks) | 0.312*** | 0.332*** | 0.357* | 0.392** | 0.563** | 0.631*** |
| | (0.089) | (0.084) | (0.180) | (0.152) | (0.248) | (0.221) |
| Ln(Underwriter Reputation) | 0.027 | 0.039 | -0.091 | -0.070 | -0.010 | 0.047 |
| | (0.124) | (0.130) | (0.195) | (0.185) | (0.207) | (0.190) |
| Ln(Assets) | -0.438*** | -0.445*** | -1.114*** | -1.126*** | -0.999*** | -1.024*** |
| | (0.090) | (0.092) | (0.181) | (0.174) | (0.221) | (0.218) |
| Ln(IPO Proceeds) | 0.216 | 0.226 | 2.159*** | 2.177*** | 1.966*** | 1.990*** |
| | (0.226) | (0.205) | (0.477) | (0.483) | (0.418) | (0.426) |
| Ln(1 + Firm Age) | -0.304* | -0.307* | -0.654*** | -0.661*** | -0.962*** | -0.977*** |
| | (0.161) | (0.153) | (0.132) | (0.134) | (0.243) | (0.263) |
| ROA | 0.104* | 0.109* | 0.391*** | 0.401*** | 0.357*** | 0.382*** |
| | (0.059) | (0.060) | (0.140) | (0.143) | (0.115) | (0.113) |
| Ln(1 + No. of Patents) | 0.140 | | 0.265 | | 0.598 | |
| | (0.173) | | (0.391) | | (0.459) | |
| Ln(1 + No. of Citations) | | 2.602 | | 4.689 | | 14.433 |
| | | (6.324) | | (7.683) | | (10.035) |
| Observations | 819 | 819 | 840 | 840 | 878 | 878 |
| Adjusted R-squared | 0.023 | 0.023 | 0.155 | 0.154 | 0.193 | 0.190 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 5: The Relation between Trademarks and the Participation of Institutional Investors in a Firm's IPO**

This table reports the OLS regression results of the effect of trademarks on the participation of institutional investors. *Ln(1 + No. of Institutional Investors)* is the natural logarithm of one plus the number of institutional investors holding IPO firm shares at the end of first fiscal quarter after the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Underpricing* is the percentage difference between the first trading day closing price and the IPO offer price. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) |
|---|---|---|
| Variables | Ln(1 + No. of Institutional Investors) | Ln(1 + No. of Institutional Investors) |
| Ln(1 + No. of Trademarks) | 0.065* | 0.060* |
| | (0.033) | (0.032) |
| Ln(Underwriter Reputation) | 0.079 | 0.081 |
| | (0.058) | (0.060) |
| Ln(Assets) | -0.032 | -0.031 |
| | (0.022) | (0.022) |
| Ln(IPO Proceeds) | 0.655*** | 0.652*** |
| | (0.080) | (0.081) |
| Ln(1 + Firm Age) | -0.018 | -0.018 |
| | (0.029) | (0.029) |
| ROA | 0.031 | 0.031 |
| | (0.033) | (0.034) |
| Underpricing | 0.189*** | 0.188*** |
| | (0.042) | (0.041) |
| Tobin's Q | -0.011*** | -0.011*** |
| | (0.003) | (0.003) |
| Ln(1 + No. of Patents) | -0.024 | |
| | (0.032) | |
| Ln(1 + No. of Citations) | | 0.134 |
| | | (1.069) |
| Observations | 662 | 662 |
| Adjusted R-squared | 0.474 | 0.474 |
| Industry FE | Yes | Yes |
| Year FE | Yes | Yes |
| State FE | Yes | Yes |

## Table 6: The Relation between Trademarks and Post-IPO Operating Performance

This table reports the OLS regression results of the effect of trademarks on the post-IPO operating performances of IPO firms. The dependent variable used in this table is *OIBDA* in year 0, 1, 2, and 3, where year 0 is the year of IPO and year 1, 2, and 3 are corresponding years after the IPO. *OIBDA* is the ratio of operating income before depreciation plus interest income (Compustat items 13 and 62, respectively) to the book value of total assets (item 6). *OIBDA* is adjusted for industry performance by subtracting contemporaneous industry (two-digit SIC code) medians. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA |
| Variables | Year 0 | Year 0 | Year 1 | Year 1 | Year 2 | Year 2 | Year 3 | Year 3 |
| Ln(1 + No. of Trademarks) | 0.014 | 0.011 | 0.036*** | 0.034*** | 0.078*** | 0.071*** | 0.100* | 0.105* |
| | (0.016) | (0.015) | (0.013) | (0.012) | (0.016) | (0.016) | (0.056) | (0.058) |
| Ln(Assets) | 0.019 | 0.019 | 0.044* | 0.044* | 0.068*** | 0.068*** | 0.103* | 0.101* |
| | (0.018) | (0.018) | (0.025) | (0.025) | (0.023) | (0.022) | (0.052) | (0.052) |
| Ln(1 + Firm Age) | 0.077** | 0.078** | 0.021 | 0.023 | 0.026 | 0.032 | 0.215 | 0.211 |
| | (0.030) | (0.031) | (0.050) | (0.051) | (0.035) | (0.039) | (0.142) | (0.140) |
| Ln(Underwriter Reputation) | 0.008 | 0.006 | 0.045*** | 0.043*** | 0.049*** | 0.045*** | -0.002 | 0.001 |
| | (0.018) | (0.018) | (0.010) | (0.011) | (0.009) | (0.010) | (0.057) | (0.057) |
| ROA | 0.023 | 0.022 | 0.021 | 0.020 | 0.056** | 0.055** | 0.081 | 0.083 |
| | (0.026) | (0.026) | (0.021) | (0.021) | (0.023) | (0.023) | (0.057) | (0.058) |
| Tobin's Q | -0.005 | -0.005 | 0.003*** | 0.003** | -0.000 | -0.001 | 0.014 | 0.015 |
| | (0.004) | (0.004) | (0.001) | (0.001) | (0.002) | (0.002) | (0.008) | (0.009) |
| Ln(1 + No. of Patents) | -0.022 | | -0.013 | | -0.038** | | 0.036 | |
| | (0.017) | | (0.012) | | (0.015) | | (0.044) | |
| Ln(1 + No. of Citations) | | -0.340 | | -0.134 | | -0.395 | | 0.648 |
| | | (0.419) | | (0.377) | | (0.357) | | (1.851) |
| Observations | 560 | 560 | 501 | 501 | 391 | 391 | 307 | 307 |
| Adjusted R-squared | 0.163 | 0.159 | 0.159 | 0.158 | 0.094 | 0.090 | 0.041 | 0.041 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 7: The Relation between Trademarks and the Information Asymmetry Facing Firms

This table reports the OLS regression results of the effect of trademarks on secondary-market information asymmetry measures. *Forecast Error* is the mean-squared error of analyst' earnings forecasts. We measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the share price at the time of forecast. *Dispersion* is the standard deviation of analysts' earnings forecasts. *No. of Analysts* is the number of analysts following a firm at the end of the fiscal year of IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation rankings, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Forecast Error | Forecast Error | Dispersion | Dispersion | No. of Analysts | No. of Analysts |
| Ln(1 + No. of Trademarks) | -0.006 | -0.007 | -0.098* | -0.099* | 0.241* | 0.308** |
| | (0.010) | (0.010) | (0.053) | (0.055) | (0.119) | (0.138) |
| Ln(Underwriter Reputation) | -0.019 | -0.020 | -0.118 | -0.112 | -0.063 | -0.026 |
| | (0.016) | (0.016) | (0.089) | (0.083) | (0.225) | (0.219) |
| Ln(Assets) | -0.003 | -0.003 | 0.016 | 0.014 | 1.141*** | 1.135*** |
| | (0.010) | (0.010) | (0.048) | (0.047) | (0.226) | (0.222) |
| Ln(1 + Firm Age) | -0.017** | -0.017* | -0.062 | -0.060 | -0.260 | -0.277 |
| | (0.008) | (0.008) | (0.066) | (0.064) | (0.164) | (0.175) |
| Tobin's Q | -0.002*** | -0.002*** | 0.004 | 0.004 | 0.091*** | 0.093*** |
| | (0.000) | (0.000) | (0.008) | (0.008) | (0.019) | (0.020) |
| Ln(1 + No. of Patents) | -0.009 | | 0.036 | | 0.460* | |
| | (0.010) | | (0.044) | | (0.229) | |
| Ln(1 + No. of Citations) | | 0.026 | | 3.513 | | 6.535 |
| | | (0.480) | | (3.725) | | (4.856) |
| Observations | 719 | 719 | 629 | 629 | 860 | 860 |
| Adjusted R-squared | 0.002 | 0.001 | 0.051 | 0.054 | 0.321 | 0.314 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 8: Instrumental Variable Analysis of the Relation between Trademarks and the Propensity for Successful Exit**

This table reports the instrumental variable regression results of successful exits of VC-backed firms on trademarks. In the first stage regression, we regress *Ln(1+No. of Trademarks)* on *Examiner Leniency* (the instrumental variable), *Ln(1 + Firm Age), Ln(Total Investment), Ln(1 + VC Age), Ln(VC Fund Size), No. of Rounds by VCs, Average No. of VCs per Round, No. of Trademark applications*, and *Ln(1 + No. of Patents)*. In the second stage regression, we use *Predicted Ln(1+No. of Trademarks)* as the main independent variable. In Columns (2) and (3), the dependent variable is a dummy variable equal to one if a private firm went public or was acquired within five years of the last round of VC investment, and zero otherwise. In Columns (4) and (5), the dependent variable is a dummy variable equal to one if a private firm went public within five years of the last round of VC investment, and zero otherwise. In Columns (6) and (7), the dependent variable is a dummy variable equal to one if a private firm was acquired within five years of the last round of VC investment, and zero otherwise. The instrumental variable, *Examiner Leniency*, is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the two-year window prior to the year of exit. *Predicted Ln(1+ No. of Trademarks)* is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression. The year of exit. is the year of IPO or acquisition for the firm, which had a successful exit. Otherwise, the year of exit. is set at five years after the last round of VC investment. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from firm founding year to the year of exit. *Ln(Total Investment)* is the natural logarithm of the total VC investments across all rounds received by a private firm. *Ln(1 + VC Age)* is the natural logarithm of one plus the number of years from lead VC founding year to the year of exit. *Ln(VC Fund Size)* is the natural logarithm of fund size of the lead VC in the year of the private firm's exit. *No. of Rounds by VCs* is the total number of rounds of VC investments received by the private firm. *Average No. of VCs per Round* is the ratio of the number of different VC firms investing in the private firm and the number of VC investment rounds in the firm. *No. of Trademark Applications* is the number of trademark applications made by a firm in the two-year window prior to the year of exit. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to the firm between five years prior to the first round of VC investment and the year of exit. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by the patents. Constant and dummy variables for two-digit SIC industry, year, state of a firm's headquarters, and lead are included in all regressions. All standard errors are clustered at the lead VC level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | First Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage |
| Variables | Ln (1+ No. of Trademarks) | IPO and M&A | IPO and M&A | IPO only | IPO only | M&A only | M&A only |
| Examiner Leniency | 0.739*** | | | | | | |
| | (0.129) | | | | | | |
| Predicted Ln (1+ No. of Trademarks) | | 1.628*** | 1.625*** | 0.164 | 0.238 | 1.371*** | 1.363*** |
| | | (0.168) | (0.169) | (0.866) | (0.852) | (0.267) | (0.265) |
| Ln(1 + Firm Age) | 0.062*** | -0.163*** | -0.169*** | 0.054 | 0.063 | -0.158*** | -0.167*** |
| | (0.020) | (0.058) | (0.058) | (0.085) | (0.085) | (0.053) | (0.052) |
| Ln(Total Investment) | -0.017 | 0.123*** | 0.113*** | 0.256*** | 0.274*** | 0.040 | 0.024 |
| | (0.014) | (0.040) | (0.040) | (0.053) | (0.053) | (0.032) | (0.032) |
| Ln(1 + VC Age) | 0.028 | -0.312 | -0.303 | -0.083 | -0.090 | -0.307** | -0.301* |
| | (0.060) | (0.211) | (0.212) | (0.258) | (0.256) | (0.153) | (0.154) |
| Ln(VC Fund Size) | 0.112*** | -1.153*** | -1.165*** | -0.574*** | -0.542*** | -0.245*** | -0.268*** |
| | (0.024) | (0.246) | (0.245) | (0.113) | (0.112) | (0.061) | (0.061) |
| No. of Rounds by VCs | -0.008 | 0.039** | 0.038** | 0.032 | 0.036* | 0.003 | -0.000 |
| | (0.006) | (0.018) | (0.018) | (0.020) | (0.020) | (0.014) | (0.014) |
| Average No. of VCs per Round | 0.001 | 0.015 | 0.014 | 0.069** | 0.068** | -0.036 | -0.036 |
| | (0.009) | (0.028) | (0.028) | (0.031) | (0.031) | (0.024) | (0.024) |
| No. of Trademark Applications | 0.036*** | -0.052*** | -0.053*** | 0.017 | 0.016 | -0.059*** | -0.060*** |
| | (0.005) | (0.011) | (0.011) | (0.030) | (0.030) | (0.010) | (0.010) |
| Ln(1 + No. of Patents) | 0.008 | -0.071 | | 0.231*** | | -0.167*** | |
| | (0.017) | (0.053) | | (0.063) | | (0.053) | |
| Ln(1 + No. of Citations) | | | 0.935 | | 3.082 | | -1.262 |
| | | | (2.240) | | (2.331) | | (1.908) |
| Observations | 2,214 | 2,214 | 2,214 | 2,129 | 2,129 | 2,480 | 2,480 |
| F Statistic from 1st Stage | 22.74 | | | | | | |
| Adjusted R-squared | 0.257 | | | | | | |
| Industry dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Lead VC dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 9: Instrumental Variable Analysis of the Relation between Trademarks and IPO and Secondary Market Valuations**

This table reports the instrumental variable regression results of the effect of trademarks on IPO and secondary valuations. In the first stage regression, we regress *Ln(1+No. of Trademarks)* on *Examiner Leniency* (the instrumental variable), *Ln(Underwriter Reputation), Ln(Assets), Ln(IPO Proceeds), Ln(1 + Firm Age), ROA, No. of Trademark applications,* and *Ln(1 + No. of Patents)*. In the second stage regression, we use *Predicted Ln(1+No. of Trademarks)* as the main independent variable. *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* are the industry-adjusted Tobin's Q ratios calculated using the IPO offer price, the first trading day close price, and the price at the end of the first post-IPO fiscal quarter, respectively. Tobin's Q is the ratio of the market value of assets to the book value of the assets, with the market value of assets equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day and the share price is the IPO offer price for *IPO valuation*, the first trading day closing price for *Secondary Valuation (FD)*, or the price at the end of first post-IPO fiscal quarter for *Secondary Valuation (FQ)*. The number of shares outstanding, share price, book value of assets, and book value of equity for the industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's two-digit standard-industrial classification code (SIC) code industry peers. *Examiner Leniency* is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the two-year window prior to the IPO. *Predicted Ln(1+ No. of Trademarks)* is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *No. of Trademark Applications* is the number of trademark applications made by a firm in the two-year window prior to the IPO. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | First Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage |
| Variables | Ln (1+ No. of Trademarks) | IPO Valuation | IPO Valuation | Secondary Valuation (FD) | Secondary Valuation (FD) | Secondary Valuation (FQ) | Secondary Valuation (FQ) |
| Examiner Leniency | 1.844*** | | | | | | |
| | (0.244) | | | | | | |
| Predicted Ln (1+ No. of Trademarks) | | 0.803 | 1.166 | 2.675*** | 2.932*** | 2.563* | 3.286** |
| | | (0.883) | (0.791) | (0.855) | (0.824) | (1.352) | (1.311) |
| Ln(Underwriter Reputation) | 0.013 | -0.143 | -0.113 | -0.172 | -0.155 | 0.112 | 0.197 |
| | (0.059) | (0.221) | (0.253) | (0.307) | (0.313) | (0.274) | (0.284) |
| Ln(Assets) | 0.068*** | -0.493*** | -0.545*** | -1.532*** | -1.567*** | -1.511*** | -1.596*** |
| | (0.021) | (0.162) | (0.168) | (0.253) | (0.258) | (0.266) | (0.275) |
| Ln(IPO proceeds) | -0.021 | 0.407 | 0.458* | 3.060*** | 3.089*** | 2.703*** | 2.750*** |
| | (0.035) | (0.286) | (0.264) | (0.550) | (0.533) | (0.442) | (0.433) |
| Ln(1 + Firm Age) | -0.000 | -0.435** | -0.427* | -1.141*** | -1.142*** | -1.485*** | -1.497*** |
| | (0.029) | (0.196) | (0.208) | (0.352) | (0.351) | (0.404) | (0.414) |
| ROA | 0.008 | 0.101* | 0.113* | 0.488 | 0.494 | 0.646** | 0.667** |
| | (0.023) | (0.053) | (0.056) | (0.302) | (0.311) | (0.250) | (0.272) |
| No. of Trademark Applications | 0.020 | -0.031 | -0.031 | -0.096* | -0.097** | -0.083 | -0.089 |
| | (0.012) | (0.026) | (0.024) | (0.046) | (0.046) | (0.057) | (0.062) |
| Ln(1 + No. of Patents) | -0.004 | 0.449** | | 0.275 | | 0.744** | |
| | (0.020) | (0.190) | | (0.182) | | (0.333) | |
| Ln(1 + No. of Citations) | | | 5.537 | | 2.449 | | 15.428 |
| | | | (9.698) | | (10.895) | | (16.086) |
| Observations | 491 | 491 | 491 | 505 | 505 | 525 | 525 |
| F Statistic from 1st Stage | 46.24 | | | | | | |
| Adjusted R-squared | 0.218 | | | | | | |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 10: Instrumental Variable Analysis of the Relation between Trademarks and the Participation of Institutional Investors in a Firm's IPO**

This table reports the instrumental variable regression results of the effect of trademarks on the participation of institutional investors. In the first stage regression, we regress *Ln(1+No. of Trademarks)* on *Examiner Leniency* (the instrumental variable), *Ln(Underwriter Reputation), Ln(Assets), Ln(IPO Proceeds), Ln(1 + Firm Age), ROA, Underpricing, Tobin's Q, No. of Trademark applications,* and *Ln(1 + No. of Patents)*. In the second stage regression, we use *Predicted Ln(1+No. of Trademarks)* as the main independent variable. *Ln(1 + No. of Institutional Investors)* is the natural logarithm of one plus the number of institutional investors holding IPO firm shares at the end of first fiscal quarter after the IPO. *Examiner Leniency* is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the two-year window prior to IPO. *Predicted Ln(1+ No. of Trademarks)* is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Underpricing* is the percentage difference between the first trading day closing price and the IPO offer price. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *No. of Trademark Applications* is the number of trademark applications made by a firm in the two-year window prior to the IPO. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| | First Stage | Second Stage | Second Stage |
| Variables | Ln (1+ No. of Trademarks) | Ln(1 + No. of Institutional Investors) | Ln(1 + No. of Institutional Investors) |
| Examiner Leniency | 2.135*** | | |
| | (0.302) | | |
| Predicted Ln(1+ No. of Trademarks) | | 0.555* | 0.563* |
| | | (0.287) | (0.302) |
| Ln(Underwriter Reputation) | 0.037 | 0.068** | 0.074*** |
| | (0.076) | (0.027) | (0.025) |
| Ln(Assets) | 0.079** | -0.023 | -0.025 |
| | (0.028) | (0.039) | (0.039) |
| Ln(IPO Proceeds) | -0.027 | 0.536*** | 0.533*** |
| | (0.037) | (0.073) | (0.071) |
| Ln(1 + Firm Age) | 0.008 | -0.036 | -0.035 |
| | (0.041) | (0.055) | (0.053) |
| ROA | -0.003 | 0.021 | 0.025 |
| | (0.038) | (0.072) | (0.076) |
| Underpricing | -0.038 | 0.243*** | 0.242*** |
| | (0.057) | (0.059) | (0.060) |
| Tobin's Q | 0.008 | -0.013** | -0.013** |
| | (0.006) | (0.005) | (0.005) |
| No. of Trademark Applications | 0.019 | -0.019*** | -0.019*** |
| | (0.012) | (0.006) | (0.006) |
| Ln(1 + No. of Patents) | -0.001 | 0.029 | |
| | (0.031) | (0.036) | |
| Ln(1 + No. of Citations) | | | 1.796 |
| | | | (1.593) |
| Observations | 406 | 406 | 406 |
| F Statistic from 1st Stage | 91.08 | | |
| Adjusted R-squared | 0.199 | | |
| Industry FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes |

## Table 11: Instrumental Variable Analysis of the Relation between Trademarks and Post-IPO Operating Performance

This table reports the instrumental variable regression results of the effect of trademarks post-IPO operating performances of IPO firms. In the first stage regression, we regress *Ln(1+No. of Trademarks)* on *Examiner Leniency* (the instrumental variable), *Ln(Assets), Ln(Underwriter Reputation), Ln(1 + Firm Age), ROA, Tobin's Q, No. of Trademark applications,* and *Ln(1 + No. of Patents)*. In the second stage regression, we use *Predicted Ln(1+No. of Trademarks)* as the main independent variable. Dependent variable used in this table is *OIBDA* in year 0, 1, 2, and 3, where year 0 is the year of IPO and year 1, 2, and 3 are the corresponding years after the IPO. *OIBDA* is the ratio of operating income before depreciation plus interest income (Compustat items 13 and 62, respectively) to the book value of total assets (item 6). *OIBDA* is adjusted for industry performance by subtracting contemporaneous industry (two-digit SIC code) medians. The instrumental variable, *Examiner Leniency*, is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the two-year window prior to IPO. *Predicted Ln(1+ No. of Trademarks)* is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *No. of Trademark Applications* is the number of trademark applications made by a firm in the two-year window prior to the IPO. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | First Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage |
| Variables | Ln (1+ No. of Trademarks) | OIBDA Year 0 | OIBDA Year 0 | OIBDA Year 1 | OIBDA Year 1 | OIBDA Year 2 | OIBDA Year 2 | OIBDA Year 3 | OIBDA Year 3 |
| Examiner Leniency | 1.382*** | | | | | | | | |
| | (0.288) | | | | | | | | |
| Predicted Ln(1+ No. of Trademarks) | | -0.018 | -0.026 | -0.304 | -0.291 | -0.217 | -0.231 | 0.908* | 0.904* |
| | | (0.129) | (0.144) | (0.360) | (0.379) | (0.524) | (0.514) | (0.509) | (0.466) |
| Ln(Assets) | 0.065* | 0.017 | 0.018 | 0.050 | 0.048 | 0.119** | 0.119** | 0.029 | 0.030 |
| | (0.032) | (0.021) | (0.022) | (0.045) | (0.045) | (0.055) | (0.053) | (0.079) | (0.079) |
| Ln(Underwriter Reputation) | -0.003 | 0.014 | 0.013 | 0.034 | 0.033 | 0.030 | 0.023 | -0.056 | -0.061 |
| | (0.062) | (0.026) | (0.025) | (0.064) | (0.064) | (0.075) | (0.076) | (0.160) | (0.160) |
| Ln(1 + Firm Age) | 0.078* | 0.070* | 0.071* | 0.035 | 0.035 | 0.060 | 0.064 | -0.016 | -0.012 |
| | (0.043) | (0.037) | (0.036) | (0.085) | (0.086) | (0.132) | (0.135) | (0.173) | (0.177) |
| ROA | 0.021 | 0.016 | 0.016 | 0.035** | 0.037** | 0.049 | 0.053 | 0.074 | 0.074 |
| | (0.025) | (0.019) | (0.020) | (0.016) | (0.016) | (0.036) | (0.037) | (0.127) | (0.128) |
| Tobin's Q | 0.011* | -0.001 | -0.001 | 0.008 | 0.008 | 0.001 | 0.001 | -0.008 | -0.010 |
| | (0.006) | (0.003) | (0.003) | (0.005) | (0.005) | (0.010) | (0.009) | (0.009) | (0.008) |
| No. of Trademark Applications | 0.019** | -0.000 | -0.000 | 0.006 | 0.005 | 0.002 | 0.001 | -0.027* | -0.027** |
| | (0.007) | (0.002) | (0.002) | (0.005) | (0.005) | (0.011) | (0.011) | (0.013) | (0.011) |
| Ln(1 + No. of Patents) | 0.033* | -0.008 | | 0.015 | | -0.027 | | -0.072* | |
| | (0.018) | (0.025) | | (0.014) | | (0.018) | | (0.040) | |
| Ln(1 + No. of Citations) | | | -0.128 | | 1.501* | | 0.689 | | -1.742 |
| | | | (0.416) | | (0.781) | | (0.915) | | (1.820) |
| Observations | 337 | 337 | 337 | 298 | 298 | 236 | 236 | 189 | 189 |
| F Statistic from 1st Stage | 93.28 | | | | | | | | |
| Adjusted R-squared | 0.286 | | | | | | | | |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

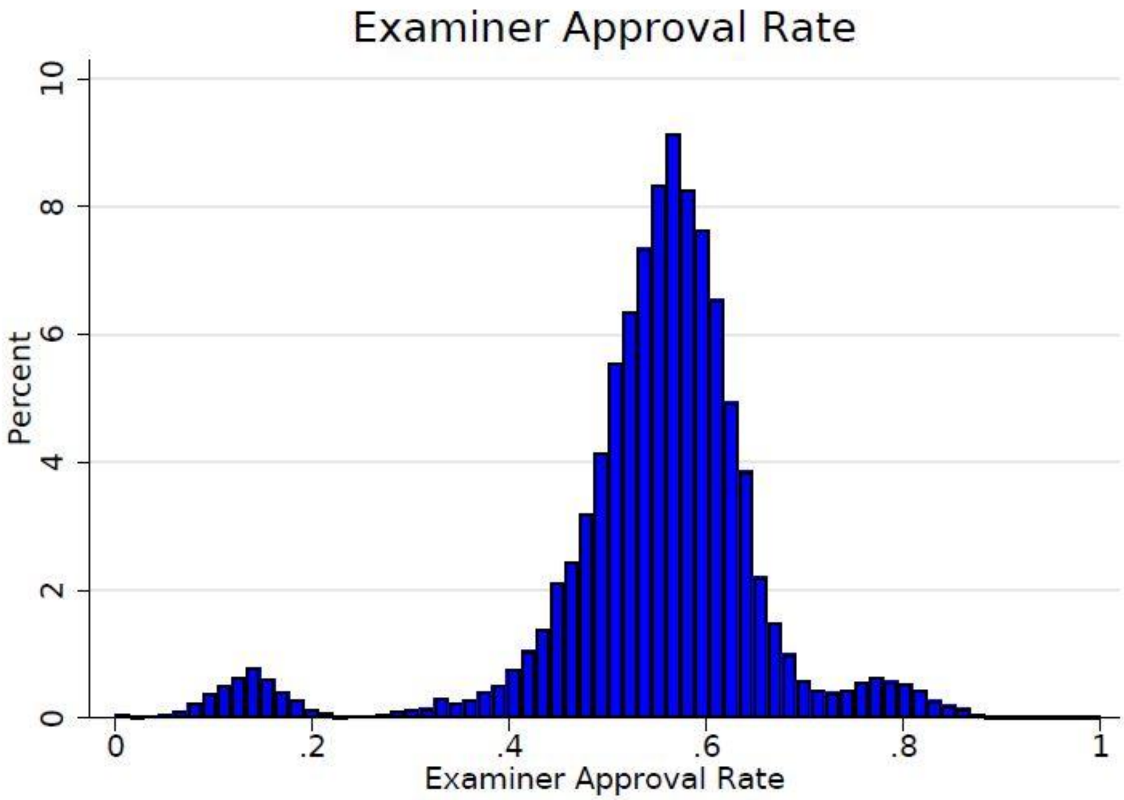
**Table 12: Instrumental Variable Analysis of the Relation between Trademarks and Information Asymmetry Facing the Firm**

This table reports the instrumental variable regression results of the effect of trademarks on secondary-market information asymmetry measures. In the first stage regression, we regress *Ln(1+No. of Trademarks)* on *Examiner Leniency* (the instrumental variable), *Ln(Underwriter Reputation), Ln(Assets), Ln(1 + Firm Age), Tobin's Q, No. of Trademark applications,* and *Ln(1 + No. of Patents)*. In the second stage regression, we use *Predicted Ln(1+No. of Trademarks)* as the main independent variable. *Forecast Error* is the mean-squared error of analysts' earnings forecastsw. We measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the price per share at the time of forecast. *Dispersion* is the standard deviation of analysts' earnings forecasts. *No. of Analysts* is the number of analysts following a firm at the end of the fiscal year of the IPO. The instrumental variable, *Examiner Leniency*, is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the two-year window prior to IPO. *Predicted Ln(1+ No. of Trademarks)* is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter reputation rankings, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *No. of Trademark Applications* is the number of trademark applications made by a firm in the two-year window prior to the IPO. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | First stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage | Second Stage |
| Variables | Ln(1+No. of Trademarks) | Forecast Error | Forecast Error | Dispersion | Dispersion | No. of Analysts | No. of Analysts |
| Examiner Leniency | 1.501*** | | | | | | |
| | (0.254) | | | | | | |
| Predicted Ln(1+ No. of Trademarks) | | -0.246** | -0.250** | -0.615 | -0.423 | 1.328 | 1.605 |
| | | (0.099) | (0.097) | (0.907) | (0.839) | (1.923) | (1.985) |
| Ln(Underwriter Reputation) | 0.016 | -0.021 | -0.020 | -0.124** | -0.109* | 0.033 | 0.064 |
| | (0.048) | (0.018) | (0.018) | (0.050) | (0.054) | (0.370) | (0.366) |
| Ln(Assets) | 0.068*** | 0.033** | 0.033** | 0.102 | 0.085 | 1.206*** | 1.178*** |
| | (0.023) | (0.014) | (0.014) | (0.091) | (0.111) | (0.330) | (0.306) |
| Ln(1 + Firm Age) | 0.060 | 0.000 | 0.001 | -0.110 | -0.131 | -0.541*** | -0.551** |
| | (0.047) | (0.022) | (0.023) | (0.079) | (0.096) | (0.185) | (0.197) |
| Tobin's Q | 0.004 | -0.002 | -0.002 | -0.004 | -0.004 | 0.074** | 0.075** |
| | (0.003) | (0.001) | (0.001) | (0.005) | (0.005) | (0.031) | (0.031) |
| No. of Trademark Applications | 0.028*** | 0.005** | 0.005** | 0.014 | 0.009 | 0.001 | -0.001 |
| | (0.002) | (0.002) | (0.002) | (0.028) | (0.030) | (0.043) | (0.045) |
| Ln(1 + No. of Patents) | 0.019 | 0.001 | | 0.056 | | 0.364 | |
| | (0.016) | (0.016) | | (0.076) | | (0.276) | |
| Ln(1 + No. of Citations) | | | 0.451 | | 6.093 | | 5.638 |
| | | | (0.872) | | (5.438) | | (5.322) |
| Observations | 438 | 438 | 438 | 382 | 375 | 530 | 530 |
| F Statistic from 1st Stage | 162.42 | | | | | | |
| Adjusted R-squared | 0.309 | | | | | | |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Figure 1: Distribution of Trademark Examiner Approval Rates**

This figure shows the sample distribution of trademark examiner approval rates, defined as in equation (7). The sample consists of all trademark data available at USPTO website until 2015.



# Internet Appendix: Propensity Score Matching Analysis

In this appendix, we present our propensity score matching analysis of the relation between the number of trademarks registered by a firm and its IPO and immediate secondary market valuations; the participation of institutional investor in its IPO; its post-IPO operating performance; and the information asymmetry facing the firm in the post-IPO equity market. While the propensity score matching analysis allows us to minimize the difference only in observable characteristics between firms with trademarks and those without any trademarks, we present our propensity score matching analysis here as additional identification mechanism secondary to our instrumental variable analysis presented in the main body of the paper.

Following the methodology of Lee and Wahal (2004), we match firms that have registered trademarks in our sample with firms that do not have any trademarks using the one-to-one "nearest neighbors" propensity score matching technique. In the first stage, we run probit regressions with the dependent variable equal to one for firms with least one trademark and zero otherwise on a set of independent (matching) variables. The matching variables include the natural logarithm of one plus the total number of class-adjusted patents, the natural logarithm of underwriter reputation, the natural logarithm of assets, the natural logarithm of one plus firm age, pre-IPO industry adjusted operating performance, industry dummies, and year dummies. Each firm with at least one trademark (treated firm) is matched with a firm without any trademark (control firm) based on the proximity of propensity score estimated from the above probit regressions. All matching is conducted with replacement.[1]

We assess the efficacy of our matched sample in Table A1. Panel A shows the comparison between treated and control firms prior to matching. Panel B compares treated and control firms after matching: we find that treated and control firms are similar across all observables after matching. After balancing the sample, we use the propensity score matched subsample to run various regressions. Since in this subsample some control firms are matched with multiple treated

[1] We have also employed the kernel and local linear regression propensity score matching techniques to conduct our analysis. The results of these alternative propensity score matching techniques are similar to the one-to-one nearest neighbor technique reported here. Due to space limitations, the results using these alternative propensity score matching techniques are not reported in order to conserve space.

firms, we use the weighted least squares (WLS) regressions in which the weight for each treated firm is one, while the weight for each control firm is equal to the number of times it is used as a match for treated firms. We find that all our WLS regression results using the propensity score matched sample are similar to our baseline OLS results documented in the main body of the paper.

## A1 Propensity Score Matching Analysis of Trademarks and IPO and Secondary Market Valuation

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and its IPO and immediate secondary market valuations. We report these results in Table A2. In Columns (1) and (2), the dependent variable is IPO valuation. We find that the coefficients of trademarks are positive and significant at the 5 percent level. In Columns (3) and (4), the dependent variable is secondary valuation computed using first day closing price. We find that the coefficients of trademarks are positive and significant at the 10 percent level. Finally, in Columns (5) and (6), we use secondary valuation computed using first post-IPO fiscal quarter price as our dependent variable. The coefficients of trademarks are positive and significant at the 1 percent level. In sum, we find that a larger number of trademarks leads to higher IPO and immediate secondary valuations, supporting our hypotheses **H4** and **H5**.

## A2 Propensity Score Matching Analysis of Trademarks and Participation of Institutional Investors in a Firm's IPO

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and participation of institutional investors in its IPO. We report these results in Table A3. In Columns (1) and (2), the dependent variable is the natural logarithm of one plus the number of institutional investors holding shares in the firm and the coefficients of trademarks are significant at the 10 percent level for both the columns. In sum, we find that a larger number of trademarks lead to greater institutional investor participation in the IPO, supporting our hypothesis **H6**.

### A3 Propensity Score Matching Analysis of Trademarks and Post-IPO Operating Performance

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and its post-IPO operating performance. We report these results in Table A4. In Columns (1) and (2), the dependent variable is the level of *OIBDA* in the year of IPO. We find that the coefficients of trademarks are positive but insignificant. We show that the coefficients of trademarks are positive and significant (at the 1 percent level) for years 1 and year 2 immediately after the IPO year (Columns (3) to (6)). However, for the third year after IPO, we find that the coefficients of trademarks are positive but insignificant (as shown in Columns (7) and (8)). Broadly, our results show that a larger number of trademarks lead to a higher level of post-IPO operating performance, consistent with our hypothesis **H7**.

### A4 Propensity Score Matching Analysis of Trademarks and the Information Asymmetry Facing the Firm in the Post-IPO Market

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and the extent of information asymmetry facing the firm in the post-IPO equity market. We report these results in Table A5. In Columns (1) and (2), the dependent variable is analyst forecast error, and we find that the coefficients of trademarks are negative but insignificant. In Columns (3) and (4), the dependent variable is analyst forecast dispersion, and the coefficients of trademarks are negative as expected and significant at the 10 percent level. In Columns (5) and (6), the dependent variable is the number of analysts covering the firm, and the coefficients of trademarks are significant at the 1 percent level. In sum, we show that a larger number of trademarks lead to a lower extent of information asymmetry facing the firm in the equity market, which lends support for our hypothesis **H8**.

## References

Lee, Peggy M., and Sunil Wahal, 2004, Grandstanding, certification and the underpricing of venture capital backed IPOs, *Journal of Financial Economics* 73, 375–407.

## Table A1: Propensity Score Matching Diagnostic Tests

This table reports the diagnostic tests of propensity score matching. Propensity score matching is implemented using the following covariates: *Ln(1 + No. of Patents), Ln(Underwriter Reputation), Ln(Assets), Ln(1 + Firm Age), ROA, 2-digit SIC* dummy, and *Year* dummy. The sample consists of 500 firms with trademarks (treatment group) and 351 firms without any trademark (control group). Panel A compares treatment and control groups on the above mentioned covariates prior to matching. Panel B compares treatment and control groups on the selected covariates post matching. Propensity score matching is implemented using the one-to-one "nearest neighbors" methodology with common support. All matching is conducted with replacement. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *2-digit SIC* is the two-digit SIC industry dummy and *Year* is the year dummy. *V(T)* and *V(C)* are the variance of treatment and control groups on different covariates, respectively.

Panel A: Pre-Match Sample Characteristics

| | Mean | | % bias | t-test | | V(T)/V(C) |
|---|---|---|---|---|---|---|
| Variable | Treated | Control | | t | p>t | |
| Ln(1 + No. of Patents) | 0.860 | 0.467 | 45.900 | 6.470 | 0.000*** | 1.540 |
| Ln(Underwriter Reputation) | 1.917 | 1.927 | -1.800 | -0.250 | 0.802 | 1.320 |
| Ln(Assets) | 3.411 | 3.355 | 3.500 | 0.510 | 0.608 | 0.710 |
| Ln(1 + Firm Age) | 2.042 | 1.847 | 26.900 | 3.990 | 0.000*** | 0.460 |
| ROA | -0.337 | -0.494 | 13.300 | 2.050 | 0.041** | 0.150 |

Panel B: Post-Match Sample Characteristics

| | Mean | | % bias | t-test | | V(T)/V(C) |
|---|---|---|---|---|---|---|
| Variable | Treated | Control | | t | p>t | |
| Ln(1 + No. of Patents) | 0.860 | 0.820 | 4.600 | 0.660 | 0.508 | 1.020 |
| Ln(Underwriter Reputation) | 1.917 | 1.972 | -10.000 | -1.630 | 0.103 | 1.580 |
| Ln(Assets) | 3.411 | 3.365 | 2.900 | 0.500 | 0.616 | 0.950 |
| Ln(1 + Firm Age) | 2.042 | 2.100 | -8.000 | -1.270 | 0.204 | 0.470 |
| ROA | -0.337 | -0.331 | -0.500 | -0.140 | 0.887 | 0.890 |

**Table A2: Propensity Score Matching Analysis of the Relation between Trademarks and IPO and Immediate Secondary Market Valuations**

This table reports the multivariate weighted least squares (WLS) regression results on the effect of trademarks on IPO and secondary market valuations using the propensity score matched sample. The weight for each firm with trademarks is equal to one, whereas the weight for each firm without any trademark is equal to the number of times it is used as a match for firms with trademarks. Propensity score matching is implemented using the one-to-one "nearest neighbors" methodology with common support. All matching is conducted with replacement. Propensity score matching is implemented using the following covariates: *Ln(1 + No. of Patents), Ln(Underwriter Reputation), Ln(Assets), Ln(1 + Firm Age), ROA, 2-digit SIC* dummy, and *year* dummy. *IPO Valuation, Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* are the industry-adjusted Tobin's Q ratios calculated using the IPO offer price, the first trading day close price, and the price at the end of the first post-IPO fiscal quarter, respectively. Tobin's Q is the ratio of the market value of assets to the book value of the assets, with the market value of assets equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day. The share price we use is the IPO offer price for *IPO Valuation*, the first trading day closing price for *Secondary Valuation (FD),* or the price at the end of first post-IPO fiscal quarter for *Secondary Valuation (FQ).* The number of shares outstanding, share price, book value of assets, and book value of equity for the industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's two-digit standard-industrial classification code (SIC) code industry peers. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the five-year period before the first round of investment. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. *Ln(1 + Firm Age)* is he natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents applied and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| Variables | (1) IPO Valuation | (2) IPO Valuation | (3) Secondary Valuation (FD) | (4) Secondary Valuation (FD) | (5) Secondary Valuation (FQ) | (6) Secondary Valuation (FQ) |
|---|---|---|---|---|---|---|
| Ln(1 + No. of Trademarks) | 0.182** | 0.199** | 0.332* | 0.337* | 0.774*** | 0.786*** |
| | (0.069) | (0.072) | (0.187) | (0.171) | (0.189) | (0.176) |
| Ln(Underwriter Reputation) | 0.185 | 0.200 | -0.090 | -0.099 | 0.115 | 0.108 |
| | (0.113) | (0.122) | (0.195) | (0.195) | (0.209) | (0.214) |
| Ln(Assets) | -0.324** | -0.330** | -1.063*** | -1.067*** | -1.050*** | -1.058*** |
| | (0.122) | (0.122) | (0.214) | (0.212) | (0.233) | (0.232) |
| Ln(IPO Proceeds) | 0.235 | 0.243 | 2.626*** | 2.654*** | 2.296*** | 2.337*** |
| | (0.272) | (0.244) | (0.661) | (0.660) | (0.576) | (0.581) |
| Ln(1 + Firm Age) | -0.010 | -0.024 | -0.498** | -0.507** | -0.880*** | -0.898*** |
| | (0.148) | (0.141) | (0.198) | (0.201) | (0.252) | (0.258) |
| ROA | -0.166* | -0.168 | 0.253* | 0.237 | 0.417 | 0.394 |
| | (0.089) | (0.101) | (0.139) | (0.139) | (0.269) | (0.278) |
| Ln(1 + No. of Patents) | 0.201** | | 0.064 | | 0.165 | |
| | (0.093) | | (0.236) | | (0.207) | |
| Ln(1 + No. of Citations) | | 3.399 | | -3.167 | | -3.102 |
| | | (5.916) | | (5.492) | | (6.194) |
| Observations | 951 | 951 | 951 | 951 | 951 | 951 |
| Adjusted R-squared | 0.109 | 0.107 | 0.229 | 0.229 | 0.244 | 0.243 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Table A3: Propensity Score Matching Analysis of the Relation between Trademarks and the Participation of Institutional Investors in a Firm's IPO**

This table reports the multivariate weighted least square (WLS) regression results on the effect of trademarks on the participation of institutional using the propensity score matched sample. The weight for each firm with trademarks is equal to one, whereas the weight for each firm without any trademark is equal to the number of times it is used as a match for firms with trademarks. Propensity score matching is implemented using the one-to-one "nearest neighbors" methodology with common support. All matching is conducted with replacement. Propensity score matching is implemented using the following covariates: *Ln(1 + No. of Patents)*, *Ln(Underwriter Reputation)*, *Ln(Assets)*, *Ln(1 + Firm Age)*, *ROA*, *2-digit SIC* dummy, and *year* dummy. *Ln(1 + No. of Institutional Investors)* is the natural logarithm of one plus the number of institutional investors holding IPO firm shares at the end of first fiscal quarter after the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO for propensity score matched regressions. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Underpricing* is the percentage difference between the first trading day closing price and the IPO offer price. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents applied and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) |
|---|---|---|
| Variables | Ln(1 + No. of Institutional Investors) | Ln(1 + No. of Institutional Investors) |
| Ln(1 + No. of Trademarks) | 0.064* | 0.059* |
| | (0.033) | (0.032) |
| Ln(Underwriter Reputation) | 0.085 | 0.084 |
| | (0.059) | (0.066) |
| Ln(Assets) | -0.021 | -0.021 |
| | (0.026) | (0.026) |
| Ln(IPO Proceeds) | 0.682*** | 0.680*** |
| | (0.079) | (0.083) |
| Ln(1 + Firm Age) | -0.066 | -0.058 |
| | (0.050) | (0.055) |
| ROA | 0.066 | 0.072 |
| | (0.043) | (0.044) |
| Underpricing | 0.149*** | 0.146*** |
| | (0.030) | (0.030) |
| Tobin's Q | -0.007 | -0.007 |
| | (0.005) | (0.005) |
| Ln(1 + No. of Patents) | -0.063 | |
| | (0.040) | |
| Ln(1 + No. of Citations) | | -0.434 |
| | | (1.142) |
| Observations | 778 | 778 |
| Adjusted R-squared | 0.523 | 0.519 |
| Industry FE | Yes | Yes |
| Year FE | Yes | Yes |
| State FE | Yes | Yes |

**Table A4: Propensity Score Matching Analysis of the Relation between Trademarks and Post-IPO Operating Performance**

This table reports the multivariate weighted least squares (WLS) regression results on the effect of trademarks on firms' post-IPO operating performances using the propensity score matched sample. The weight for each firm with trademarks is to one, whereas the weight for each firm without any trademark is equal to the number of times it is used as a match for firms with trademarks. Propensity score matching is implemented using the one-to-one "nearest neighbors" methodology with common support. All matching is conducted with replacement. Propensity score matching is implemented using the following covariates: *Ln(1 + No. of Patents)*, *Ln(Underwriter Reputation)*, *Ln(Assets)*, *Ln(1 + Firm Age)*, *ROA*, *2-digit SIC* dummy, and *year* dummy. Dependent variable used in this table is *OIBDA* in year 0, 1, 2, and 3, where year 0 is the year of IPO and year 1, 2, and 3 are corresponding years after the IPO. *OIBDA* is the ratio of operating income before depreciation plus interest income (Compustat items 13 and 62, respectively) to the book value of total assets (item 6). *OIBDA* is adjusted for industry performance by subtracting contemporaneous industry (two-digit SIC code) medians. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO adjusted for contemporaneous median *ROA* of the two-digit SIC code industry peers. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents applied and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA | OIBDA |
| Variables | Year 0 | Year 0 | Year 1 | Year 1 | Year 2 | Year 2 | Year 3 | Year 3 |
| Ln(1 + No. of Trademarks) | 0.017 | 0.017 | 0.044*** | 0.044*** | 0.181*** | 0.179*** | 0.067 | 0.069 |
| | (0.015) | (0.015) | (0.011) | (0.011) | (0.035) | (0.035) | (0.067) | (0.069) |
| Ln(Assets) | 0.002 | 0.001 | 0.077 | 0.077 | 0.054 | 0.052 | 0.019 | 0.023 |
| | (0.015) | (0.015) | (0.052) | (0.052) | (0.069) | (0.070) | (0.033) | (0.031) |
| Ln(1 + Firm Age) | 0.057* | 0.059* | -0.026 | -0.026 | 0.023 | 0.022 | -0.048 | -0.046 |
| | (0.028) | (0.030) | (0.054) | (0.055) | (0.066) | (0.073) | (0.114) | (0.111) |
| Ln(Underwriter Reputation) | 0.001 | -0.001 | 0.095** | 0.094** | 0.088*** | 0.091*** | 0.048 | 0.048 |
| | (0.013) | (0.013) | (0.042) | (0.041) | (0.026) | (0.024) | (0.082) | (0.084) |
| ROA | 0.223*** | 0.226*** | 0.100*** | 0.102*** | 0.217*** | 0.229*** | 0.278*** | 0.272*** |
| | (0.012) | (0.011) | (0.026) | (0.023) | (0.037) | (0.043) | (0.092) | (0.091) |
| Tobin's Q | -0.006 | -0.006 | 0.002 | 0.002 | -0.028*** | -0.028*** | 0.007* | 0.006* |
| | (0.005) | (0.005) | (0.002) | (0.002) | (0.007) | (0.005) | (0.004) | (0.004) |
| Ln(1 + No. of Patents) | -0.009 | | 0.005 | | 0.044 | | -0.037 | |
| | (0.013) | | (0.015) | | (0.049) | | (0.024) | |
| Ln(1 + No. of Citations) | | 0.270 | | 0.405 | | 2.822 | | -2.105** |
| | | (0.529) | | (0.816) | | (2.016) | | (0.850) |
| Observations | 578 | 578 | 491 | 491 | 416 | 416 | 311 | 311 |
| Adjusted R-squared | 0.433 | 0.433 | 0.268 | 0.268 | 0.267 | 0.272 | 0.211 | 0.215 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table A5: Propensity Score Matching Analysis of the Relation between Trademarks and the Information Asymmetry Facing the Firm**

This table reports the multivariate weighted least squares (WLS) regression results on the effect of trademarks on secondary-market information asymmetry measures using the propensity score matched sample. The weight for each firm with trademarks is equal to one, whereas the weight for each firm without any trademark is equal to the number of times it is used as a match for firms with trademarks. Propensity score matching is implemented using the one-to-one "nearest neighbors" methodology with common support. All matching is conducted with replacement. Propensity score matching is implemented using the following covariates: *Ln(1 + No. of Patents)*, *Ln(Underwriter Reputation)*, *Ln(Assets)*, *Ln(1 + Firm Age)*, *ROA*, *2-digit SIC* dummy, and *year* dummy. *Forecast Error* is the mean-squared error of analysts' earnings forecast. We measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the price per share at the time of forecast. *Dispersion* is the standard deviation of analysts' earnings forecasts. *No. of Analysts* is the number of analysts following a firm at the end of the fiscal year of the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation rankings, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Tobin's Q* is the industry adjusted *Tobin's Q* computed using the first trading day closing price. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents applied and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

| Variables | (1) Forecast Error | (2) Forecast Error | (3) Dispersion | (4) Dispersion | (5) No. of Analysts | (6) No. of Analysts |
|---|---|---|---|---|---|---|
| Ln(1 + No. of Trademarks) | -0.015 | -0.015 | -0.150* | -0.142* | 0.378*** | 0.426*** |
| | (0.015) | (0.014) | (0.074) | (0.069) | (0.129) | (0.142) |
| Ln(Underwriter Reputation) | -0.034*** | -0.034*** | -0.237 | -0.213 | -0.357** | -0.341** |
| | (0.011) | (0.007) | (0.170) | (0.138) | (0.145) | (0.124) |
| Ln(Assets) | 0.011 | 0.011 | 0.044 | 0.037 | 1.100*** | 1.092*** |
| | (0.017) | (0.017) | (0.043) | (0.042) | (0.177) | (0.176) |
| Ln(1 + Firm Age) | -0.040*** | -0.040*** | -0.267** | -0.268** | -0.558*** | -0.557*** |
| | (0.011) | (0.011) | (0.127) | (0.126) | (0.140) | (0.145) |
| Tobin's Q | -0.002** | -0.002** | 0.006 | 0.006 | 0.094*** | 0.097*** |
| | (0.001) | (0.001) | (0.006) | (0.005) | (0.023) | (0.023) |
| Ln(1 + No. of Patents) | -0.002 | | 0.122 | | 0.446 | |
| | (0.024) | | (0.124) | | (0.275) | |
| Ln(1 + No. of Citations) | | -0.136 | | 6.492 | | 2.315 |
| | | (1.270) | | (8.274) | | (7.923) |
| Observations | 764 | 764 | 764 | 764 | 764 | 764 |
| Adjusted R-squared | 0.124 | 0.124 | 0.209 | 0.213 | 0.358 | 0.350 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |