

# Trademarks in Entrepreneurial Firm Success: Empirical Evidence from Venture Backed Private Firms and Initial Public Offerings

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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); Valuation; Private Firm Exit; Post-IPO Operating Performance

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# 1 Introduction

Trademarks are an important determinant of the economic value created by firms.<sup>1</sup> 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.<sup>2</sup>

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.”<sup>3</sup> Second, trademarks may convey credible (but possibly noisy) information about future

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<sup>1</sup>For example, in a survey of high-tech firms covered by VentureXpert by Graham, Merges, Samuelson, and Sichelman (2009) on the importance of trade secrets, patents, copyrights, and trademarks for entrepreneurial firm success, respondents viewed trademarks as moderately important. In particular, for VC-backed software firms, the importance of trademarks and that of patents were viewed as statistically indistinguishable from each other.

<sup>2</sup>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.

<sup>3</sup>One real world example is Harry’s, a VC-backed start-up that manufactures and sells shaving products. Harry’s

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 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).<sup>4</sup> 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.<sup>5</sup> 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

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registered multiple trademarks for its name, logo, and service. This has been considered as part of Harry’s successful branding strategy, which helps Harry’s to build trust and encourage repeat sales and to obtain 4.3% of America’s razor market share from large competitors such as Gillette.

<sup>4</sup>As we argue in our theory and hypotheses development section, there are direct and indirect costs associated with the trademark application process and maintenance. For example, there is a substantial cost involved in the trademark opposition process (any person/entity with real interest in proceedings can oppose a trademark application when it is published for opposition during the application process and attempt to stop it from registration). Citing the 2013 Report of Economic Survey by American Intellectual Property Law Association (AIPLA), Gaddis, Garboczi, Stewartson, and Reid (2015) mention that the median cost to a party in trademark opposition is \$80,000. Given the substantial costs involved in the trademark application process and maintenance, it is reasonable to hypothesize that trademarks are noisy signals of quality. Consistent with the substantial costs involved in the trademark application process, we find empirical evidence that only about 15% of VC-backed firms have at least one trademark in the five years before receiving the first round of VC investment, although around 47 % of these firms have at least one trademark by the time of exit. We discuss the costs involved in the trademark application process in more detail in Sections 3 and 4 of this paper.

<sup>5</sup>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 titled “Do Venture Capitalists Care about Intellectual Property?” in *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).

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 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 informational 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 primarily 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 measures (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 1,048 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 obtain 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% (0.27 million dollars) increase in the total funding for a 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% 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 3.1 percentage point increase in the probability of successful exit, where a successful exit is either through an IPO or an 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.<sup>6</sup>

We now summarize the results of our second set of empirical tests which analyze the relation

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<sup>6</sup>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.

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 8% and 7.3% average increase in IPO and immediate secondary market valuations, respectively (as measured by their Tobin's Q). 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 0.2% average increase in the number of institutional investors investing in firms. 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 0.051 in *OIBDA* (the ratio of operating income before depreciation plus interest income to the book value of total assets). This increase is substantial, given that the median value of *OIBDA* in the first year after IPO is -0.15. 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% decrease in the mean dispersion in analyst forecasts and a 6% increase in the average analyst coverage. 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 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. We therefore use an instrumental variable (IV) analysis to establish causality.<sup>7</sup> We instrument for the number of trademarks registered by a firm using a measure

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<sup>7</sup>We also address the endogeneity concerns using a propensity score matching analysis, which is presented in an

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. Specifically, we instrument for the number of granted trademarks using the average examiner leniency calculated across all the trademark applications (accepted or rejected) made by a 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 institutional details of the trademark application process and associated costs. Section 5 describes our data and sample selection procedures. Section 6 presents our empirical analyses and results. Section 7 concludes. The results of our propensity-score matching analyses and additional analysis validating our IV are presented in an Online Appendix (not to be published).

## 2 Relation to the Existing Literature and Contribution

Our paper is related to several strands in the literature. One strand in the literature related 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, as well as their valuation at IPO and their post-IPO operating performance. Block, De Vries, Schumman, and Sandner (2014) show that the number and breadth of trademarks have inverted U-shaped relation with financial valuation of start-ups by VCs.<sup>8</sup> Our paper is also related to papers analyzing the relation between the patents held by private firms at IPO, their IPO valuation, and

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Online 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.

<sup>8</sup>Zhou, Sandner, Martinelli, and Block (2016) show that patents and trademarks have a direct and complementary effect on VC financing.

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 the number of patents held by VC-backed firms at IPO and their post-IPO stock returns.

In contrast to the above literature, ours is the first paper 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.<sup>9</sup>

Our paper also contributes to several strands in the broader entrepreneurial finance and the IPO 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

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<sup>9</sup>Our paper is also related, though more distantly, to the empirical literature on corporate innovation. In particular, it is related to the literature analyzing how VC-backing (and the type of VC backing entrepreneurial firms, namely, corporate or independent VC) affects innovation in newly public firms: see, e.g., Tian and Wang (2014) and Chemmanur, Loutskina, and Tian (2014). In contrast to the above literature, the focus of our paper is to analyze the channels through which an important alternative form of intellectual property other than patents, namely trademarks, affect firm success, even after accounting for the effect of patents.



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.<sup>10</sup> 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). Our paper contributes indirectly to this strand in the literature by showing, for the first time, that an important determinant of private firm success is the portfolio of trademarks held by them.

Finally, our paper is also related to the literature on the role of trademarks, patents, and other forms of intellectual property in established (seasoned) firms.<sup>11</sup> 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 (2019) find that stronger trademark protection has negative effect on innovation and product quality. Unlike the above papers that focus on the role of trademarks in established firms, the focus of our paper is on how trademarks help the performance of private firms and firms going public.

### 3 Theory and Hypotheses 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).<sup>12</sup> 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

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<sup>10</sup>Bhattacharya and Ritter (1983) argue that firms face trade-off between disclosing their private information about R&D activities versus raising external finance at better terms after disclosing their private information. See Ritter and Welch (2002) for an excellent review of the theoretical and empirical literature on IPOs.

<sup>11</sup>For an excellent review of the economics of intellectual property, see Besen and Raskind (1991).

<sup>12</sup>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 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 of trademarks.<sup>13</sup>

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).<sup>14</sup> 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

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<sup>13</sup>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.

<sup>14</sup>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.

portfolio.<sup>15</sup> We will refer to this role of trademarks as their “informational” role.<sup>16</sup>

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 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.<sup>17</sup>

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.

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<sup>15</sup>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.

<sup>16</sup>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).

<sup>17</sup>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 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**).

#### 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.<sup>18</sup> 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

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<sup>18</sup>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.

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**).

## **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 relation 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 relation between the number of trademarks held by a firm and its valuation at the IPO offer price. This relation 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)).<sup>19</sup> Since 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**).

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<sup>19</sup>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 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.

### 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 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 relation 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 Trademark Applications: Institutional Detail

According to 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.<sup>20</sup> Upon filing the application, the USPTO checks for the minimum filing requirements and assigns a serial number to the application provided that the application meets the filing criteria. After the assignment, the USPTO appoints an examining attorney to review the application. The USPTO explicitly mentions on their website that applications are randomly assigned to examining attorneys and are examined in the order in which

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<sup>20</sup>Note that the trademark application and evaluation process is completely distinct from the patent application and evaluation process and is handled by a separate division of the USPTO.

they are received by the USPTO.<sup>21</sup> 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, she will approve the application for publication.<sup>22</sup> Otherwise, she will issue an office action explaining grounds for rejection or suggest minor corrections if required. The most common ground for refusing registration is the existence of a “likelihood of confusion” between the applicant’s mark and the mark in an existing registration by another firm.<sup>23</sup> Other grounds for refusal include that the proposed mark is generic or merely descriptive, geographic, a surname, deceptive, among other things. If the examining attorney raises no objections to registration, or if the applicant overcomes all objections, the examining attorney will approve the mark for publication in the “Official Gazette,” a weekly publication of the USPTO. The USPTO will send a notice of publication to the applicant stating the date of publication. After the mark is published in the “Official Gazette,” any party who believes it may be damaged by the registration of the mark has 30 days from the publication date to file either an opposition to the registration or a request to extend the time to oppose. An opposition is similar to a proceeding in a federal court, but is held before the Trademark Trial and Appeal Board (TTAB), an administrative tribunal within the USPTO. If no opposition is filed or if the opposition is unsuccessful, the application enters the next stage of the registration process.<sup>24</sup> It can take three to four months from the time the notice of publication is sent till the applicant receives an official notice of the next status of the application.

After getting a trademark registration, the registration owner must file required maintenance documents on a regular basis to keep the registration alive. Failure to file the required maintenance documents during the specified time periods will result in the cancellation of the trademark registration or invalidation of the extension of protection in the U.S. To maintain its trademark

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<sup>21</sup>Please refer to following document by Graham, Hancock, Marco, and Myers (2013) for more detail regarding the trademark application process and datasets: <https://www.uspto.gov/learning-and-resources/electronic-data-products/trademark-case-files-dataset-0>. To quote Graham, Hancock, Marco, and Myers (2013): “In general, applications are randomly assigned to examining attorneys and examined in the order in which they are received by the USPTO.”

<sup>22</sup>Unlike patent examiners who specialize in certain areas (“art-units”), the USPTO mentions on their website that various law offices examining trademarks currently do not specialize in examining trademarks in any particular subject matter.

<sup>23</sup>The likelihood of confusion should only bar registration when the earlier mark is owned by an entity other than applicant.

<sup>24</sup>Please refer to the USPTO website for additional information on the application process: <https://www.uspto.gov/trademarks-getting-started/trademark-process#step5>.



registration, a firm must file its first maintenance document between the fifth and sixth year after the registration date and other maintenance documents thereafter. It is important to note that it is the responsibility of a firm to police and enforce its trademark rights. While the USPTO will prevent another pending application for a similar mark used on related goods or in connection with related services from proceeding to registration based on a finding of likelihood of confusion, the USPTO will not engage in any separate policing or enforcement activities of trademarks.

#### 4.1 Costs Associated with Trademarks

As we argued in Section 3, there are direct and indirect costs associated with the trademark application process and maintenance. First, regarding the direct costs of filing trademark applications, the USPTO website provide details of the specific amount that firms must pay for each class of goods/services. For example, if the application of a mark will be used in different classes, then the application fee will be counted towards all classes, with \$200-\$400 for each class. Thus, the total application fee itself may be a few thousand dollars for each trademark application. Further, a trademark requires maintenance as well, which will cost a few thousand dollars every year. As explained on the USPTO website, although anyone can apply for a trademark, trademark application does include multiple steps that require significant work, such as selecting marks, identifying mark formats, identifying goods and services, searching, and checking filing basis. Therefore, the USPTO suggests that applicants should consider hiring a trademark attorney with the preparation and the application process overall.

Second, there are substantial indirect costs associated with trademark applications and maintenance. There is a substantial cost involved in the trademark opposition process (any person/entity with real interest in the proceedings may oppose a trademark application when it is published for opposition during the application process and attempt to stop it if from registration). Citing the 2013 Report of Economic Survey by the American Intellectual Property Law Association (AIPLA), Gaddis, Garboczi, Stewartson, and Reid (2015) mention that the median cost to a party in trademark opposition is \$80,000.<sup>25</sup> Further, this white paper mentions that attorneys' fees are not recoverable in these cases even if the opposition is frivolous. They claim that frivolous trademark oppositions are a real problem facing small businesses and entrepreneurs, who cannot bear

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<sup>25</sup>See more details on the trademark opposition cost at: [https://tlpc.colorado.edu/wp-content/uploads/2015/05/TMOppositionReform\\_WhitePaper3.pdf](https://tlpc.colorado.edu/wp-content/uploads/2015/05/TMOppositionReform_WhitePaper3.pdf).

the financial costs of defending an opposition under the current USPTO rules. It is even possible that smaller firms may simply abandon their trademark applications under the threat of opposition. Additionally, it is the responsibility of the firm to enforce its trademark rights by monitoring unfair usage of its trademarks by rivals, which may involve substantial monitoring and potential litigation costs. According to the 2013 Report of the Economic Survey by AIPLA, the total costs of trademark infringement litigation on average are as follows: \$375,000 through trial when less than \$1 million is at issue; \$794,000 when \$1-10 million is at issue; \$1.4 million when \$10-25 million is at issue; and \$2 million in costs when the amount at issue exceeds \$25 million.<sup>26</sup>

Based on the aforementioned direct and indirect costs associated with the trademark application process and maintenance, it is reasonable to assume that firms will file for trademarks only if the expected benefits from trademarks exceed the expected costs associated with them, and that firms will likely avoid filing frivolous trademark applications. Consistent with the substantial costs involved in the trademark application process, our empirical evidence shows that only about 15% of VC-backed firms have at least one trademark in the five years before receiving the first round of VC investment, although around 47% of these firms have at least one trademark by the time of exit. This revealed preference by firms may indicate that there are costs involved with obtaining and maintaining trademarks and that firms register their trademarks only if the benefits outweigh the costs.

## 5 Data and Sample Selection

### 5.1 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 24,512 distinct entrepreneurial firms in the U.S. We identify lead VC investor for each entrepreneurial firm following Nahata (2008)

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<sup>26</sup>More details on trademark litigation are available at: <http://www.ipwatchdog.com/2015/07/16/trademark-bullying-defending-your-brand-or-vexatious-business-tactics/id=59155/>.

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, Panel B, and Panel C 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 24,512 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 D of Table 1 provides summary statistics for our sample of VC-backed firms that eventually went public.

## 5.2 Measures of Trademarks

We obtain the list of all the trademark applications available in the USPTO database (USPTO trademark case file dataset) from 1982 to 2015.<sup>27</sup> This includes all the applications whether they were granted (i.e., registered trademarks), pending, or abandoned (application that is no longer pending and, thus, cannot mature into registration). The case files also contain the names of examining attorneys who examine the trademark applications. 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

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<sup>27</sup>Graham, Hancock, Marco, and Myers (2013) claim that the coverage of trademark applications is comprehensive after 1982 in the USPTO case file dataset.

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 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 logged measure ( $\ln(1 + \text{No. of Trademarks})$ ) 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 trademark. Panel A of Table 1 reports summary statistics for the trademark measure at the time of the first round of VC investment. Panel D of Table 1 reports summary statistics of trademarks for public firms at time of IPO. Finally, Panel E of table 1 provides summary statistics of trademark applications and trademark examiners.

### 5.3 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,  $\ln(1+No. \text{ of Patents})$ , 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,  $\ln(1+No. \text{ of Citations})$ , 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 D of Table 1 reports the summary statistics of class-adjusted patents and citations for public firms in the year of IPO.

## 5.4 Summary Statistics

Table 1 reports the summary statistics for VC-backed private firms.<sup>28</sup> Panel A shows that an average firm in our sample receives nearly half (54%) of the total VC funding in the first round and typically receives three rounds of VC investments. Further, an average firm typically has two VC investors investing in the first round. Around 15.3% of firms have at least one trademark in the five years before receiving the first round of VC investment, while 14.6% of firms have at least one patent, and 3.5% of firms have both patent(s) and trademark(s). However, as we show in Panel C, a significant number of firms have patents and trademarks by the time of exit (IPO or acquisition or write-off): 47.4% of firms have at least one trademark and 28.6% of firms have at least one patent. Around 20% of firms have both patent(s) and trademark(s) at the time of exit.

In Panel B, we present the summary statistics of the eventual exits of VC-backed private firms.

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<sup>28</sup>Note that all the variables are winsorised at the 1st and 99th percentile.

Out of 24,512 private firms in our sample, 7,287 (29.7%) had a successful exit via acquisition, 2,106 (8.6%) had a successful exit via IPO, and the rest did not have an exit.<sup>29</sup> Panel D reports summary statistics for key IPO characteristics of venture-backed firms that eventually went public. By the time of IPO, around 58% of firms (going public) have at least one trademark while 52% have at least one patent; 35.8% of firms have both patent(s) and trademark(s).

Lastly, in Panel E, we present the summary statistics of trademark applications and registered trademarks for firms at the time of exit. We compute the lag between the filing of a trademark and the actual outcome using a dataset containing around 6 million trademark applications from 1982 to 2015 available on the USPTO website. Trademark applications take around 600 days on average from filing to final outcome. The median lag is 480 days. In total, there are 1,043 different examining attorneys (examiners) who review trademark applications.<sup>30</sup> We compute an yearly measure of their leniency or the percentage of applications approved by them. The average examiner approval rate is around 54%. We also measure the number of trademark applications filed and registered by a firm in a two year period before exit. An average firm files around four trademark applications in the two year period before exit or write-off.

## 6 Empirical Analyses and Results

### 6.1 Methodology and Identification

We empirically test the relation between trademarks and VC investment patterns, successful exit of VC-backed firms, IPO, and post-IPO characteristics. We first use ordinary least square regressions (OLS) to establish correlation between trademarks and the above mentioned firm outcomes. However, it may be argued that the relations established using our baseline analyses between the 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 relation documented between the number of trademarks and the probability of successful private firm exit may be due to higher firm quality rather than the number of trademarks held by the firm. In other words, the unobservable firm quality may be driving our

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<sup>29</sup>If a VC-backed firm did not receive any VC investment in the five years after the last VC-investment, we treat it as a case of “no exit” or consider it as an equivalent to a write-off.

<sup>30</sup>We only consider examiners who have reviewed a minimum of 10 applications in a given year.

results. To address such concerns, 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.<sup>31</sup> Our IV analysis approach builds on similar applications in the literature.<sup>32</sup> We describe the construction of our instrument in detail in the next subsection.

## 6.2 Instrumental Variable: Average Examiner Leniency

We use the average examiner leniency as an instrument for the number of trademarks granted to a firm. As described in Section 4, the USPTO stated that on their website that trademark applications are randomly assigned to trademark examining attorneys (examiners), who review these applications in the order in which they are received by the USPTO, and the examiners determine whether registration of these applications are 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.<sup>33</sup> 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 can be an endogenous choice of a firm. For example, some firms that are able to apply for trademarks may choose not to do so. Therefore, in our IV analyses, we only focus on firms that have applied for trademarks (with varying degrees of success). In other words, we consider firms that have made at least one trademark application. The success rate of a trademark application will depend on the quality of the application and the leniency of examiner.<sup>34</sup> 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. Our IV analyses exploit the exogenous variation in leniency of trademark examiners (randomly assigned) that affect the outcome of trademark applications. Further, the leniency of

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<sup>31</sup>Graham, Hancock, Marco, and Myers (2013) state that trademark examining attorneys do not specialize in particular subject matters even though they may have separate law offices.

<sup>32</sup>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 (2019) and Farre-Mensa, Hegde, and Ljungqvist (2019) use patent examiner leniency as an instrument for patent grants in their research.

<sup>33</sup>Refer to our Section 4 for details on trademark application process; also refer to Graham, Hancock, Marco, and Myers (2013) for a detailed study on the life-cycle of trademark applications.

<sup>34</sup>By quality of application, we refer to the information provided by applicant in the application, which may help to distinguish its mark from existing marks owned by other entities.

examiner is unlikely to be correlated with either firm or trademark quality.<sup>35</sup> As mentioned in Section 5, we have information on the applications, their outcomes, and corresponding examiners from the trademark case files available on the USPTO website. We then compute a time-varying measure of the leniency of each individual examiner. Specifically, the approval rate of examiner  $j$  assigned to review a trademark application  $k$  made by a firm  $i$  in year  $t$  is defined as follows:

$$Individual\ Examiner\ Leniency_{ijkt} = \frac{Grants_{jt} - Grant_k}{Applications_{jt} - 1}, \quad (1)$$

where  $Grants_{jt}$  and  $Applications_{jt}$  are the numbers of trademark granted and applications reviewed, respectively, by examiner  $j$  in the same application year as application  $k$ .<sup>36</sup>  $Grant_k$  denotes the outcome of an application  $k$  and takes the value of 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 (e.g., Maestas, Mullen, and Strand (2013)). 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).<sup>37</sup> 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 ( $Avg\ Leniency_{it}$ ) for a firm  $i$  in year  $t$ , as follows:

$$Avg\ Leniency_{it} = \frac{1}{n_i} \sum_j Individual\ Examiner\ Leniency_{ijkt}, \quad (2)$$

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 :

$$Ln(1+No.\ of\ Trademarks)_{it} = \alpha_1 Avg\ Leniency_{it} + \alpha_2 Applications_{it} + \alpha_3 X_{it} + \epsilon_{it}. \quad (3)$$

$$Outcome_{it} = \beta_1 Ln(1+No.\ of\ Trademarks)_{it} + \beta_2 Applications_{it} + \beta_3 X_{it} + \epsilon_{it}. \quad (4)$$

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<sup>35</sup>We show in Table A1 of our Online Appendix that our examiner leniency measure is uncorrelated with firm characteristics.

<sup>36</sup>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.

<sup>37</sup>We choose a two-year window to analyze the number of trademark applications made by a firm since an application on average takes around two years (600 days) before it is either accepted or abandoned. Thus, mechanically our instrument may not capture any re-submission of a rejected application. We show statistics on application lag in the Panel E of our Table 1.



In the first-stage regression (equation (3)), we regress  $\ln(1+No. \text{ of Trademarks})_{it}$  on the instrument ( $Avg \text{ Leniency}_{it}$ ), i.e., the average examiner leniency computed for firm  $i$ .<sup>38</sup>  $\ln(1+No. \text{ of Trademarks})_{it}$  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 used in prior tests.<sup>39</sup> Equation (4) 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.

### 6.2.1 *Relevance Condition*

We make use of a subsample of 5,925,040 trademark applications filed from 1982 to 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 (1)), from which we observe significant variation in the examiners' approval rates: the median examiner yearly approval rate is 56% and the interquartile range is 11.6%.

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. In all these first-stage regressions, we find that the coefficients of the instrument are positive and highly significant at the 1 percent level. We report the Kleibergen-Paap rk Wald F statistics in the first stage of all instrumental variable regressions. 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 relevance condition required for a valid instrument.

### 6.2.2 *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

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<sup>38</sup>We use the average examiner leniency across multiple applications as an instrument rather than the leniency of the examiner reviewing the first trademark application made by a firm since a firm may apply for multiple trademarks and all of them may be important for the firm's future performance.

<sup>39</sup>Our instrumental variable regression results hold even if we do not use the number of trademark applications as a control variable. However, we believe that controlling for application is appropriate since both the number of application and examiner leniency affect the number of trademarks granted to a firm.

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. We also show in Table A1 in our Online Appendix that our instrument, trademark examiners' leniency, is uncorrelated with firm, investor, and investment characteristics. 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.<sup>40</sup>

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

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:

$$Var_{it} = \alpha_0 + \alpha_1 Ln(1 + No. \text{ of Trademarks})_{it} + X_{it} + \epsilon_{it}, \quad (5)$$

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  $Ln(Investment \text{ in Round } 1)$ , defined as the natural logarithm of the total VC investments in the first round in a private firm. The second measure is  $Ln(Total \text{ Investment})$ ,

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<sup>40</sup>One may be concerned about the use of average examiner leniency as our instrument, since a firm may keep resubmitting a rejected trademark application by making slight changes in each new application. If this is the case, one would expect to find a positive correlation between the leniency of the examiner of a firm's first application and its subsequent applications. However, in an untabulated analysis, we find that this is not the case: we do not find any correlation between the examiner leniency of the first trademark application of a firm and its subsequent trademark applications. Furthermore, we show in Table A1 that average examiner leniency is uncorrelated to firm or investor characteristics, thus ruling out the above concern.

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  $\text{Ln}(1+\text{No. of Trademarks})$ .

$X$  represents a vector of control variables. In particular, we include either class-adjusted patents ( $\text{Ln}(1+\text{No. Patents})$ ) or citations ( $\text{Ln}(1+\text{No. Citations})$ ) to control for the effect of firm-innovation on VC investment size or staging. We also control for the age of a private firm ( $\text{Ln}(1+\text{Firm Age})$ ), the number of VC investors in the first round (*Syndicate Size*), the age of the lead VC ( $\text{Ln}(1+\text{VC Age})$ ), and the fund size of the lead VC ( $\text{Ln}(\text{VC Fund Size})$ ). 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 ( $\text{Ln}(\text{Investment Round 1})$ ) 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 ( $\text{Ln}(\text{Total Investment})$ ) 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% (\$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% 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**.

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

We conduct baseline and instrumental variable analyses to study the relation between trademarks and successful exit by VC-backed private firms.

### 6.4.1 Baseline Analysis

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 linear probability model:

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

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)).

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 also 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.<sup>41</sup> 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 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 1 percent level) in Column (4). 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 3.1 percentage points, 0.68 percentage point, and 3.1 percentage points 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**.

#### 6.4.2 *Instrumental Variable Analysis*

Here, we run a two-stage linear probability regression model (similar to the two stage tests shown in equations (3) and (4)) and use measures of successful exits as the dependent variable in the

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<sup>41</sup>We control for the age of a private firm ( $\ln(1+\text{Firm Age})$ ) 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 ( $\ln(\text{Total Investment})$ ) as it is an indicator of VCs’ perception of the firm. We control for the age of the lead VC ( $\ln(1+\text{VC Age})$ ) as experienced VCs are better in selecting high quality firms to invest. We also control for the fund size of the lead VC ( $\ln(\text{VC Fund Size})$ ) 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.

second stage. Note that our baseline and instrumental variable analyses are robust to using a probit model. We include the same controls and dummy variables as in our corresponding baseline linear probability 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 likely have more registered trademarks.

We report the results of these regressions in Table 4.<sup>42</sup> In Column (1), we report the first-stage regression result of our IV analysis, which corresponds to a successful exit through either an IPO or an acquisition. 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 29.60 and the adjusted R-squared is 25.7%, suggesting that our instrument satisfies the relevance condition for a valid instrument. Note that here we only report the first-stage regression result when controlling for patent counts. The first-stage regression result controlling for citations confirms that the relevance condition of our instrument is also met in this specification but is not reported due to space constraints. We adopt the same fashion when reporting the first-stage regression results of our IV analysis in later tables as well. We report the second-stage regression results of the effect of trademarks on private firms' successful exits 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. Thus, our IV analysis results show that the positive relation between trademarks on the likelihood of successful exits of VC-backed private firms is causal, lending strong support to our hypothesis **H3**.

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<sup>42</sup>Note that the sample size for our IV analysis is smaller than that for our OLS analysis, since it contains firms that have made at least one trademark application. Our OLS analysis, which provides external validation, includes all firms irrespective of them having trademarks or not.

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

### 6.5.1 Baseline Analysis

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

$$Valuation_{it} = \alpha_0 + \alpha_1 Ln(1 + No. \text{ of Trademarks})_{it} + X_{it} + \epsilon_{it}, \quad (7)$$

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 (equal to the book value of assets minus the book value of equity plus market capitalization) over the book value of assets. We measure IPO market valuation using the IPO offer price. We measure the secondary market valuation using two different measures: using first trading day closing price and using the share price at the end of the first post-IPO fiscal quarter. We construct Tobin's Q ratios for our three valuation measures, *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation(FQ)*.<sup>43</sup>

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, firm age, and operating performance in the previous year. 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 may be correlated across observations in the same industry.

We present our results of the above tests in Table 5. 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 the first day closing price. The coefficients of trademarks in these regressions are positive and significant at the 5 percent level. Finally, in Columns (5) and (6), our dependent variable is the secondary market valuation computed using the share price at the end of the first post-IPO fiscal quarter.<sup>44</sup> Here also, the coefficients of trademarks are positive and significant at

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<sup>43</sup>The book value of assets and the book value of equity for IPO firms 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.

<sup>44</sup>If we remove trademarks as the main independent variable, we find that the coefficients of patents are positive

the 5 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 0.31, 0.37, and 0.58 for *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* respectively. These increases are equivalent to 8%, 7.3%, and 10.2% average increase in *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)*, 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, supporting our hypotheses **H4** and **H5**.

### 6.5.2 Instrumental Variable Analysis

We report our IV regression results of the effects of trademarks on IPO and secondary market valuations in Table 6. In Column (1), we present the first-stage regression results of our IV analysis, which corresponds to IPO valuations (corresponding second stages shown in Columns (2) and (3)). 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 43.799 and the adjusted R-squared is 22.2%, 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 and significant at the 10 percent level (in Column (3)). In Columns (4) and (5), we use a firm's secondary market valuation computed using the 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 (at the 5 percent level in Column (7)). Thus, our IV analysis results show that trademarks have a positive and causal effect on firm valuation, which supports our hypothesis **H4**.

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and significant. However, the correlation between trademarks and patents is small, which is around 0.2.



## 6.6 The Effect of Trademarks on the Participation of Institutional Investors in a Firm’s IPO

### 6.6.1 Baseline Analysis

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:

$$MP_{it} = \alpha_0 + \alpha_1 \ln(1 + \text{No. of Trademarks})_{it} + X_{it} + \epsilon_{it}, \quad (8)$$

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 ( $\ln(1 + \text{No. of Institutional Investors})$ ) as the dependent variable. The explanatory variable of interest in our regressions is our trademark measure. 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, firm size, total IPO proceeds, firm age, underpricing, and Tobin’s Q.<sup>45</sup> 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 7. 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 0.2 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**.

### 6.6.2 Instrumental Variable Analysis

We report our IV regression results of the effects of trademarks on the participation of institutional investors in a firm’s IPO in Table 8. In Column (1), we show the first-stage regression results of

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<sup>45</sup>We control for underwriter reputation ( $\ln(\text{Underwriter Reputation})$ ) as the involvement of more reputable underwriters will attract market players in the IPO. We control for *underpricing* as Aggarwal, Krigman, and Womack (2002) show that managers use underpricing to improve demand for the stock. We control for *Tobin’s Q* since firms that have received higher valuations are likely to have greater participation by institutional investors.

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 51.714 and the adjusted R-squared is 20.4%, 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 ( $\ln(1 + \text{No. of Institutional Investors})$ ). We find that the coefficients of our trademark measure are positive and significant at the 10 percent level. Thus, 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**.

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

### 6.7.1 Baseline Analysis

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:

$$OP_{it} = \alpha_0 + \alpha_1 \ln(1 + \text{No. of Trademarks})_{it} + X_{it} + \epsilon_{it}. \quad (9)$$

where the dependent variable  $OP_{it}$  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 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).<sup>46</sup> This measure is constructed for the following four years post-IPO (i.e., year 1, 2, 3, and 4). The explanatory variable of interest in our regressions is our trademark measure. In particular, we control for corporate innovation using either class-adjusted patents or citations since they may have an impact on operating performance. Our other control variables include underwriter reputation ( $\ln(\text{Underwriter Reputation})$ ), firm size ( $\ln(\text{Assets})$ ), firm age ( $\ln(1 + \text{Firm Age})$ ), and *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 9. We find that for the three years after IPO,

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<sup>46</sup>Our results are robust to adjusting the operating performance of a firm with respect to its respective industry operating performance.

the coefficients of trademarks are positive and significant (in Columns (1) to (6)). For the year 4 after IPO, the results are in the right direction but insignificant. In terms of economic magnitude, a one standard deviation increase in our trademark measure is associated with an increase of 0.051 in *OIBDA* in the first year after IPO. This increase is substantial, given that the mean value of *OIBDA* in the first year after IPO is -0.15. 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**.

### 6.7.2 Instrumental Variable Analysis

We report our IV regression results of the effect of trademarks on a firm's post-IPO operating performance in Table 10. We report the second-stage results in Columns (1)-(8).<sup>47</sup> In Columns (1)-(8), we use *OIBDA* in the years 1, 2, 3, and 4 after IPO as dependent variables. We find that the coefficients of our trademark measure are positive and significant at the 10 percent level for the post-IPO operating performance in year 3 and year 4 (Columns (5), (6) and (7)). 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**.

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

### 6.8.1 Baseline Analysis

In this subsection, 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:

$$Asymmetry_{it} = \alpha_0 + \alpha_1 Ln(1 + No. \text{ of Trademarks})_{it} + X_{it} + \epsilon_{it}, \quad (10)$$

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 the mean squared error as the absolute

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<sup>47</sup>Due to space limitations, we do not report the first stage results here. Our first stage results are relevant and significant and are available from the authors upon request.

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. We control for innovation using either class-adjusted patents or citations as they may affect the information asymmetry facing a firm. We also control for underwriter reputation ( $\ln(\text{Underwriter Reputation})$ ), firm size ( $\ln(\text{Assets})$ ), firm age ( $\ln(1 + \text{Firm Age})$ ), and *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 11. 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% 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 6% increase in the average *No. of Analysts*.

### 6.8.2 Instrumental Variable Analysis

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, which corresponds to forecast error as a measure of information asymmetry (corresponding second stages shown in Columns (2) and (3)). 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 34.87 and the adjusted R-squared is 30.8%, 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 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. All variables are winsorised at 1 and 99 percentile. 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.  $\ln(\text{Investment in Round 1})$  is the natural logarithm of the total VC investments received by a private firm in the first round.  $\ln(\text{Total Investment})$  is the natural logarithm of the total VC investments across all rounds received by a private firm. All investments are in millions of dollars. *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. *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.  $\ln(1 + \text{Firm Age})$  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.  $\ln(1 + \text{VC Age})$  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.  $\ln(\text{VC Fund Size})$  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*. In Panel C, we show the number of patents and trademarks at the time of exit (IPO or acquisition or write-off). *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 exit. *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 exit. *Total No. of Citations* is the total number of forward citations received by these patents. The sample in Panel D 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 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)*. *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. *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. *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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{IPO Proceeds})$  is the natural logarithm of IPO proceeds.  $\ln(1 + \text{Firm Age})$  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. *Tobin's Q* is the *Tobin's Q* computed using the first trading day closing price. Finally, in Panel E, we show summary statistics of examiner leniency and trademark applications made by firms. *Application Lag (days)* is the number of days between filing of an application and outcome (registration or abandonment of application). We report this statistic for the entire universe of trademark applications filed between 1982 and 2015. *Examiner Leniency (Annual)* is the yearly measure of examiner leniency described in equation (1). *Number of Applications (Exit)* is the total number of trademark applications made by VC-backed private firms in two years before the exit year. *Number of Trademarks (Exit)* is the number of trademarks granted in the two years prior to exit year of the firm. *Number of Applications (IPO)* is the total number of trademark applications made by VC-backed private

firms in two years before the IPO year. *Number of Trademarks (IPO)* is the number of trademarks granted in the two years prior to IPO year of a firm.

Panel A: Summary Statistics at the Time of First Round of Investment in Private Firms					
Variables	N	Mean	Std. Dev.	Min	Max
Fraction of Investment in Round 1	20,637	0.54	0.401	0	1
No. of Rounds by VCs	20,637	3.233	2.59	1	23
Ln(Investment in Round 1)	20,637	0.978	1.451	-6.908	4.025
Ln(Total Investment)	20,637	2.177	1.669	-6.908	5.25
No. of Trademarks	24,512	0.371	1.135	0	7
No. of Patents	24,512	0.405	1.339	0	9
No. of Citations	24,512	4.091	19.669	0	150
Ln(1 + Firm Age)	19,221	1.057	0.98	0	4.043
Syndicate Size	24,512	2.035	1.323	1	7
Ln(1 + VC Age)	17,696	2.322	0.885	0	4.22
Ln(VC Fund Size)	17,913	5.671	1.696	1.386	9.329

Panel B: Exit Status of VC-backed Private Firms		
Status	N	Percent
Acquired	7,287	29.73
Went Public	2,106	8.59
No Exit	15,119	61.68
Total	24,512	100

Panel C: Trademarks and Patents at the exit of Private Firms					
Variables	N	Mean	Std. Dev.	Min	Max
No. of Trademarks	24,512	2	3.888	0	23
No. of Patents	24,512	2.122	6.165	0	41
No. of Citations	24,512	12.954	53.773	0	398

Panel D: Characteristics of VC-backed IPO Firms					
Variables	N	Mean	Std. Dev.	Min	Max
IPO Valuation	895	3.806	3.699	0.278	52.97
Secondary Valuation(FD)	992	5.111	5.825	0.278	69.053
Secondary Valuation(FQ)	1,043	5.643	6.777	0.529	81.119
Number of Analyst	1,013	3.842	3.837	0	29
No. of Institutional Investors	763	32.501	22.361	2	109
No. of Trademarks	1,048	3.088	4.777	0	23
No. of Patents	1,048	6.052	10.738	0	41
Total No. of Citations	1,048	55.42	114.206	0	397
Ln(Underwriter Reputation)	1,048	1.919	0.555	0	2.197
Ln(Assets)	970	3.373	1.565	-2.154	9.476
Ln(IPO Proceeds)	981	3.995	0.877	-1.386	6.864
Ln(1 + Firm Age)	1,032	1.952	0.713	0	4.248
ROA	999	-0.12	0.33	-2.39	1.08
Tobin's Q	992	5.111	5.825	0.278	69.053

Panel E: Summary Statistics of Examiner Leniency and Applications					
Variables	N	Mean	Std. Dev.	Min	Max
Application Lag (days)	5,925,040	599.462	399.625	1	9887
Examiner Leniency (Annual)	10,531	0.544	0.149	0	1
Number of Applications (Exit)	4,546	4.25	5.05	1	30
Number of Trademarks (Exit)	4,546	0.96	1.68	0	10
Number of Applications (IPO)	547	6.325	6.816	1	36
Number of Trademarks (IPO)	547	1.004	1.732	0	10

**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.

<b>Panel A: The Effect of Trademarks on the Size of VC Investment</b>				
Variables	(1) Ln(Investment in Round 1)	(2) Ln(Investment in Round 1)	(3) Ln(Total Investment)	(4) Ln(Total Investment)
Ln(1 + No. of Trademarks)	0.136*** (0.025)	0.146*** (0.025)	0.043 (0.028)	0.064** (0.028)
Ln(1 + Firm Age)	0.172*** (0.015)	0.176*** (0.015)	-0.096*** (0.015)	-0.089*** (0.015)
Syndicate Size	0.277*** (0.008)	0.278*** (0.009)	0.172*** (0.008)	0.175*** (0.009)
Ln(1 + VC Age)	-0.072 (0.058)	-0.075 (0.058)	-0.058 (0.057)	-0.063 (0.058)
Ln(VC Fund Size)	0.283*** (0.043)	0.284*** (0.044)	0.139*** (0.039)	0.139*** (0.039)
Ln(1 + No. of Patents)	0.204*** (0.038)		0.340*** (0.045)	
Ln(1 + No. of Citations)		9.805*** (2.860)		11.840*** (3.724)
Observations	11,676	11,676	11,676	11,676
Adjusted R-squared	0.423	0.422	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

<b>Panel B: The Effect of Trademarks on the Staging of VC Investment</b>				
	(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*** (0.008)	0.030*** (0.008)	-0.237*** (0.049)	-0.210*** (0.049)
Ln(1 + Firm Age)	0.072*** (0.004)	0.071*** (0.004)	-0.317*** (0.027)	-0.307*** (0.027)
Syndicate Size	0.008*** (0.002)	0.007*** (0.002)	0.059*** (0.018)	0.063*** (0.018)
Ln(1 + VC Age)	0.006 (0.013)	0.006 (0.013)	0.042 (0.103)	0.038 (0.103)
Ln(VC Fund Size)	0.019** (0.009)	0.019** (0.009)	-0.070 (0.066)	-0.070 (0.066)
Ln(1 + No. of Patents)	-0.062*** (0.012)		0.398*** (0.081)	
Ln(1 + No. of Citations)		-0.710 (1.001)		8.314 (6.909)
Observations	11,676	11,676	11,676	11,676
Adjusted R-squared	0.332	0.330	0.262	0.261
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 linear probability model (LPM) regression results of successful exits of VC-backed firms on trademarks. In Columns (1) and (2), the dependent variable takes the value one if a private firm goes public or is acquired, and zero otherwise. In Columns (3) and (4), the dependent variable takes the value one if a private firm goes public, and zero otherwise. In Columns (5) and (6), the dependent variable takes the value one if a private firm is acquired, and zero otherwise. An IPO or acquisition is regarded as a case of successful exit if it happens within five years of the last round of VC investment; otherwise, the dependent variable takes the value zero.  $\ln(1 + \text{No. of Trademarks})$  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 exit year. The exit year is the year of IPO or acquisition for a firm, which had a successful exit. Otherwise, the exit year is set at five years after the last round of VC investment.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the exit year.  $\ln(\text{Total Investment})$  is the natural logarithm of the total VC investments across all rounds received by a private firm.  $\ln(1 + \text{VC Age})$  is the natural logarithm of one plus the number of years from the founding year of the lead VC to the exit year.  $\ln(\text{VC Fund Size})$  is the natural logarithm of fund size of the lead VC at the year of exit.  $\text{No. of Rounds by VCs}$  is the total number of rounds of VC investments received by a private firm.  $\text{Average No. of VCs per Round}$  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.  $\ln(1 + \text{No. of Patents})$  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 exit year.  $\ln(1 + \text{No. of Citations})$  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 headquarter fixed effects, and 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.

Variables	(1) IPO and M&A	(2) IPO and M&A	(3) IPO only	(4) IPO only	(5) M&A only	(6) M&A only
$\ln(1 + \text{No. of Trademarks})$	0.036*** (0.006)	0.045*** (0.006)	0.001 (0.004)	0.008** (0.004)	0.036*** (0.006)	0.037*** (0.006)
$\ln(1 + \text{No. of Patents})$	0.082*** (0.007)		0.067*** (0.006)		0.015* (0.008)	
$\ln(1 + \text{No. of Citations})$		2.063*** (0.301)		1.386*** (0.304)		0.676* (0.366)
$\ln(1 + \text{Firm Age})$	-0.006 (0.006)	-0.004 (0.006)	0.010** (0.004)	0.012*** (0.004)	-0.016*** (0.006)	-0.016*** (0.006)
$\ln(\text{Total Investment})$	0.044*** (0.004)	0.047*** (0.004)	0.027*** (0.003)	0.029*** (0.003)	0.017*** (0.004)	0.018*** (0.004)
$\ln(1 + \text{VC Age})$	-0.039 (0.026)	-0.046* (0.026)	-0.009 (0.016)	-0.015 (0.016)	-0.030 (0.023)	-0.031 (0.023)
$\ln(\text{VC Fund Size})$	-0.356*** (0.014)	-0.354*** (0.014)	-0.173*** (0.012)	-0.172*** (0.012)	-0.183*** (0.015)	-0.182*** (0.015)
No. of Rounds by VCs	-0.007*** (0.002)	-0.006*** (0.002)	0.000 (0.002)	0.001 (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
Average No. of VCs per Round	0.004 (0.003)	0.005 (0.003)	0.008*** (0.003)	0.010*** (0.003)	-0.004 (0.003)	-0.004 (0.003)
Observations	12,932	12,932	12,932	12,932	12,932	12,932
Adjusted R-squared	0.232	0.226	0.153	0.142	0.101	0.101
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	Yes	Yes	Yes	Yes	Yes	Yes

**Table 4: Instrumental Variable Analysis of the Relation between Trademarks and Propensity for Successful Exit**

This table reports the linear probability model (LPM) regression results of successful exits of VC-backed firms on trademarks using an instrumental variable. In the first stage regression  $\ln(1 + \text{No. of Trademarks})$  is regressed on *Examiner Leniency*,  $\ln(1 + \text{Firm Age})$ ,  $\ln(\text{Total Investment})$ ,  $\ln(1 + \text{VC Age})$ ,  $\ln(\text{VC Fund Size})$ , *No. of Rounds by VCs*, *Average No. of VCs per Round*, *No. of Trademark applications*, and  $\ln(1 + \text{No. of Patents})$ . In the second stage we use *Predicted  $\ln(1 + \text{No. of Trademarks})$*  as an independent variable. In Columns (2) and (3), the dependent variable takes the value one if a private firm goes public or is acquired, and zero otherwise. In Columns (4) and (5), the dependent variable takes the value one if a private firm goes public, and zero otherwise. In Columns (6) and (7), the dependent variable takes the value one if a private firm is acquired, and zero otherwise. An IPO or acquisition is regarded as a case of successful exit if it happens within five years of the last round of VC investment; otherwise, the dependent variable takes the value zero. *Examiner Leniency* is the examiner leniency averaged over all the trademark applications filed by firms in the prior two-year window before their exit or *No Exit*.  $\ln(1 + \text{No. of Trademarks})$  is the natural logarithm of one plus the total number of trademarks that a firm has registered in the two-year window leading to the year of exit. *Predicted  $\ln(1 + \text{No. of Trademarks})$*  is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression. The exit year is the year of IPO or acquisition for the firm, which had a successful exit. Otherwise, the exit year is set at five years after the last round of VC investment.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from firm founding year to the exit year.  $\ln(\text{Total Investment})$  is the natural logarithm of the total VC investments across all rounds received by a private firm. All investments are in millions of dollars.  $\ln(1 + \text{VC Age})$  is the natural logarithm of one plus the number of years from lead VC founding year to the exit year.  $\ln(\text{VC Fund Size})$  is the natural logarithm of fund size of the lead VC at the year of exit. Fund size is in millions of dollars. *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 leading to the year of exit.  $\ln(1 + \text{No. of Patents})$  is the natural logarithm of one plus the total adjusted number of patents applied and eventually granted to the firm between five years prior to the first round of VC investment and the exit year.  $\ln(1 + \text{No. of Citations})$  is the natural logarithm of one plus the total adjusted number of forward citations received by the patents. Constant, two-digit SIC industry fixed effects, year fixed effects, state of a firm's headquarter fixed effects, and 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.



Variables	(1)	(2)		(3)	(4)		(5)	(6)		(7)
	First Stage Ln (1 + No. of Trademarks)	Second Stage IPO and M&A		Second Stage IPO and M&A	Second Stage IPO only		Second Stage IPO only	Second Stage M&A only		Second Stage M&A only
Examiner Leniency	0.739*** (0.129)									
Predicted Ln (1 + No. of Trademarks)		0.685*** (0.193)		0.679*** (0.192)	0.077 (0.149)		0.088 (0.148)	0.922*** (0.325)		0.917*** (0.326)
Ln(1 + Firm Age)	0.062*** (0.020)	-0.064*** (0.023)		-0.065*** (0.023)	0.005 (0.016)		0.007 (0.016)	0.019 (0.028)		0.018 (0.028)
Ln(Total Investment)	-0.017 (0.014)	0.052*** (0.014)		0.050*** (0.014)	0.040*** (0.011)		0.044*** (0.011)	0.030* (0.018)		0.028 (0.018)
Ln(1 + VC Age)	0.028 (0.060)	-0.101* (0.061)		-0.100 (0.061)	0.024 (0.050)		0.021 (0.050)	-0.095 (0.067)		-0.095 (0.067)
Ln(VC Fund Size)	0.112*** (0.024)	-0.275*** (0.030)		-0.275*** (0.030)	-0.156*** (0.027)		-0.150*** (0.028)	0.012 (0.034)		0.011 (0.034)
No. of Rounds by VCs	-0.008 (0.006)	0.011* (0.006)		0.011* (0.006)	0.011** (0.005)		0.012** (0.005)	0.000 (0.007)		-0.000 (0.007)
Average No. of VCs per Round	0.001 (0.009)	0.006 (0.010)		0.005 (0.010)	0.019** (0.007)		0.019** (0.007)	-0.019* (0.011)		-0.019* (0.011)
No. of Trademark Applications	0.036*** (0.005)	-0.023*** (0.007)		-0.023*** (0.007)	0.003 (0.006)		0.003 (0.006)	-0.029*** (0.009)		-0.029*** (0.009)
Ln(1 + No. of Patents)	0.008 (0.017)	-0.017 (0.020)			0.057*** (0.014)			-0.013 (0.026)		
Ln(1 + No. of Citations)				0.386 (0.716)			0.947 (0.677)			0.413 (0.870)
Observations	2,808	2,808		2,808	2,808		2,808	2,808		2,808
F Statistic from 1st Stage	29.60									
Adjusted R-squared	0.257									
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
Lead VC FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes

**Table 5: 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 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)*.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{IPO Proceeds})$  is the natural logarithm of IPO proceeds.  $\ln(1 + \text{Firm Age})$  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.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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)
$\ln(1 + \text{No. of Trademarks})$	0.322*** (0.078)	0.339*** (0.080)	0.390** (0.174)	0.424** (0.155)	0.606** (0.244)	0.678*** (0.224)
$\ln(\text{Underwriter Reputation})$	0.024 (0.125)	0.028 (0.131)	-0.108 (0.228)	-0.100 (0.221)	0.001 (0.230)	0.049 (0.218)
$\ln(\text{Assets})$	-0.393*** (0.075)	-0.396*** (0.076)	-0.892*** (0.183)	-0.897*** (0.180)	-0.821*** (0.207)	-0.829*** (0.211)
$\ln(\text{IPO Proceeds})$	0.282 (0.178)	0.294* (0.159)	2.184*** (0.498)	2.206*** (0.507)	1.953*** (0.455)	1.976*** (0.470)
$\ln(1 + \text{Firm Age})$	-0.192 (0.203)	-0.193 (0.199)	-0.523*** (0.185)	-0.526*** (0.180)	-0.845*** (0.233)	-0.851*** (0.243)
ROA	-1.006 (0.707)	-1.035 (0.754)	-1.674 (1.358)	-1.729 (1.424)	-0.978 (1.432)	-1.081 (1.517)
$\ln(1 + \text{No. of Patents})$	0.086 (0.136)		0.189 (0.331)		0.556 (0.383)	
$\ln(1 + \text{No. of Citations})$		0.132 (6.081)		0.640 (5.620)		11.502 (7.817)
Observations	823	823	845	845	883	883
Adjusted R-squared	0.059	0.058	0.182	0.181	0.217	0.215
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 6: 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  $\ln(1 + \text{No. of Trademarks})$  on *Examiner Leniency* (the instrumental variable),  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(\text{IPO Proceeds})$ ,  $\ln(1 + \text{Firm Age})$ , *ROA*, *No. of Trademark applications*, and  $\ln(1 + \text{No. of Patents})$ . In the second stage regression, we use *Predicted  $\ln(1 + \text{No. of Trademarks})$*  as the main independent variable. *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* are the 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)*. *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.  $\ln(1 + \text{No. of Trademarks})$  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  $\ln(1 + \text{No. of Trademarks})$*  is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{IPO Proceeds})$  is the natural logarithm of IPO proceeds.  $\ln(1 + \text{Firm Age})$  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. *No. of Trademark Applications* is the number of trademark applications made by a firm in the two-year window prior to the IPO.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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)	(2)	(3)	(4)	(5)	(6)	(7)
	First Stage Ln(1+No. of Trademarks)	Second Stage IPO Valuation	Second Stage Secondary Valuation	Second Stage Secondary Valuation (FD)	Second Stage Secondary Valuation (FQ)	Second Stage Secondary Valuation (FQ)	Second Stage Secondary Valuation (FQ)
Examiner Leniency	1.837*** (0.278)						
Predicted Ln (1+ No. of Trademarks)		1.178 (0.965)	1.515* (0.868)	2.859*** (0.960)	3.101*** (0.938)	2.459 (1.490)	3.196** (1.428)
Ln(Underwriter Reputation)	0.009 (0.059)	-0.152 (0.264)	-0.130 (0.294)	-0.184 (0.360)	-0.177 (0.365)	0.075 (0.313)	0.154 (0.330)
Ln(Assets)	0.065*** (0.023)	-0.444*** (0.150)	-0.485*** (0.159)	-1.231*** (0.274)	-1.260*** (0.276)	-1.171*** (0.333)	-1.243*** (0.346)
Ln(IPO Proceeds)	-0.034 (0.030)	0.550** (0.251)	0.614** (0.232)	3.010*** (0.521)	3.051*** (0.500)	2.481*** (0.439)	2.544*** (0.428)
Ln(1 + Firm Age)	0.002 (0.033)	-0.300 (0.222)	-0.286 (0.228)	-1.041*** (0.320)	-1.039*** (0.320)	-1.490*** (0.378)	-1.492*** (0.389)
ROA	0.189 (0.111)	-1.697** (0.633)	-1.843*** (0.632)	-1.240 (0.924)	-1.335 (0.972)	1.014 (1.002)	0.818 (1.085)
No. of Trademark Applications	0.020 (0.012)	-0.047* (0.025)	-0.048* (0.024)	-0.107** (0.042)	-0.109** (0.041)	-0.080 (0.057)	-0.087 (0.062)
Ln(1 + No. of Patents)	0.002 (0.018)	0.375* (0.199)		0.210 (0.191)		0.711** (0.301)	
Ln(1 + No. of Citations)			1.891 (9.807)		-1.707 (9.764)		11.917 (14.732)
Observations	495	495	495	510	510	530	530
F Statistics from 1st Stage	43.799						
Adjusted R-squared	0.222						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

**Table 7: 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.  $\ln(1 + \text{No. of Institutional Investors})$  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.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{IPO Proceeds})$  is the natural logarithm of IPO proceeds.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Underpricing* is the percentage difference between the first trading day closing price and the IPO offer price. *Tobin's Q* is the ratio of market and book value of assets computed using the first trading day closing price.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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)	(2)
	$\ln(1 + \text{No. of Institutional Investors})$	
$\ln(1 + \text{No. of Trademarks})$	0.061* (0.030)	0.056* (0.029)
$\ln(\text{Underwriter Reputation})$	0.066 (0.056)	0.067 (0.058)
$\ln(\text{Assets})$	-0.012 (0.018)	-0.011 (0.018)
$\ln(\text{IPO proceeds})$	0.641*** (0.079)	0.638*** (0.080)
$\ln(1 + \text{Firm Age})$	-0.004 (0.029)	-0.004 (0.029)
Underpricing	0.188*** (0.043)	0.187*** (0.043)
Tobin's Q	-0.010*** (0.003)	-0.010*** (0.003)
$\ln(1 + \text{No. of Patents})$	-0.024 (0.033)	
$\ln(1 + \text{No. of Citations})$		0.009 (0.992)
Observations	679	679
Adjusted R-squared	0.476	0.476
Industry FE	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes

**Table 8: 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  $\ln(1 + \text{No. of Trademarks})$  on *Examiner Leniency* (the instrumental variable),  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(\text{IPO Proceeds})$ ,  $\ln(1 + \text{Firm Age})$ , *Underpricing*, *Tobin's Q*, *No. of Trademark applications*, and  $\ln(1 + \text{No. of Patents})$ . In the second stage regression, we use *Predicted  $\ln(1 + \text{No. of Trademarks})$*  as the main independent variable.  $\ln(1 + \text{No. of Institutional Investors})$  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.  $\ln(1 + \text{No. of Trademarks})$  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  $\ln(1 + \text{No. of Trademarks})$*  is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{IPO Proceeds})$  is the natural logarithm of IPO proceeds.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Underpricing* is the percentage difference between the first trading day closing price and the IPO offer price. *Tobin's Q* is the ratio of market and book value of assets 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.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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)	
Examiner Leniency	2.096*** (0.291)		
Predicted Ln(1+ No. of Trademarks)		0.560* (0.275)	0.565* (0.291)
Ln(1 + No. of Patents)	-0.004 (0.031)	0.025 (0.036)	
Ln(1 + No. of Citations)			1.641 (1.387)
Ln(Underwriter Reputation)	0.040 (0.071)	0.045 (0.030)	0.050 (0.029)
Ln(Assets)	0.077*** (0.026)	-0.011 (0.038)	-0.010 (0.038)
Ln(IPO proceeds)	-0.036 (0.037)	0.527*** (0.081)	0.522*** (0.078)
Ln(1 + Firm Age)	0.013 (0.038)	-0.026 (0.051)	-0.026 (0.049)
Underpricing	-0.035 (0.053)	0.248*** (0.058)	0.247*** (0.057)
Tobin's Q	0.008 (0.006)	-0.013** (0.006)	-0.013** (0.006)
No. of Trademark Applications	0.020 (0.012)	-0.018*** (0.006)	-0.018*** (0.006)
Observations	416	416	416
F Statistic from 1st Stage	51.714		
Adjusted R-squared	0.204		
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

**Table 9: 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 1, 2, 3 and 4, where year 1 is the first year immediately after IPO and year 2, 3, and 4 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).  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Tobin's Q* is the ratio of market and book value of assets computed using the first trading day closing price.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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							
Variables	Year 1		Year 2		Year 3		Year 4	
$\ln(1 + \text{No. of Trademarks})$	0.054*** (0.011)	0.052*** (0.010)	0.090*** (0.018)	0.084*** (0.018)	0.117** (0.054)	0.126** (0.056)	0.075 (0.045)	0.072 (0.042)
$\ln(\text{Assets})$	0.065*** (0.018)	0.065*** (0.018)	0.101*** (0.024)	0.100*** (0.023)	0.154** (0.056)	0.153** (0.057)	0.106*** (0.026)	0.106*** (0.026)
$\ln(1 + \text{Firm Age})$	0.012 (0.047)	0.013 (0.047)	0.020 (0.034)	0.024 (0.037)	0.189 (0.117)	0.182 (0.114)	0.053 (0.065)	0.058 (0.064)
$\ln(\text{Underwriter Reputation})$	0.041*** (0.010)	0.039*** (0.011)	0.048*** (0.006)	0.044*** (0.008)	-0.020 (0.052)	-0.020 (0.052)	0.073 (0.076)	0.073 (0.077)
Tobin's Q	0.001 (0.002)	0.001 (0.002)	-0.002 (0.003)	-0.002 (0.003)	0.015* (0.008)	0.015* (0.008)	-0.001 (0.004)	-0.001 (0.003)
$\ln(1 + \text{No. of Patents})$	-0.014 (0.011)		-0.038** (0.018)		0.033 (0.039)		0.003 (0.025)	
$\ln(1 + \text{No. of Citations})$		-0.175 (0.569)		-0.671 (0.553)		0.027 (1.516)		0.527 (1.136)
Observations	510	510	397	397	317	317	263	263
Adjusted R-squared	0.270	0.269	0.181	0.178	0.045	0.044	0.223	0.224
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 10: 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  $\ln(1 + \text{No. of Trademarks})$  on *Examiner Leniency* (the instrumental variable),  $\ln(\text{Assets})$ ,  $\ln(\text{Underwriter Reputation})$ ,  $\ln(1 + \text{Firm Age})$ , *Tobin's Q*, *No. of Trademark applications*, and  $\ln(1 + \text{No. of Patents})$ . In the second stage regression, we use *Predicted  $\ln(1 + \text{No. of Trademarks})$*  as the main independent variable. Dependent variable used in this table is *OIBDA* in year 1, 2, 3 and 4, where year 1 is the first year immediately after IPO and year 2, 3, and 4 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). 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.  $\ln(1 + \text{No. of Trademarks})$  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  $\ln(1 + \text{No. of Trademarks})$*  is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\ln(1 + \text{Firm Age})$  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 ratio of market and book value of assets 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.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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.



**Table 11: 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.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation rankings, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(1 + \text{Firm Age})$  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 ratio of market and book value of assets computed using the first trading day closing price.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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)	(2)	(3)	(4)	(5)	(6)
	Forecast Error		Dispersion		No. of Analysts	
$\ln(1 + \text{No. of Trademarks})$	-0.006 (0.010)	-0.007 (0.010)	-0.098* (0.053)	-0.098* (0.055)	0.243* (0.120)	0.310** (0.139)
$\ln(\text{Underwriter Reputation})$	-0.019 (0.016)	-0.020 (0.016)	-0.118 (0.089)	-0.112 (0.083)	-0.061 (0.223)	-0.024 (0.217)
$\ln(\text{Assets})$	-0.003 (0.010)	-0.003 (0.010)	0.016 (0.048)	0.014 (0.047)	1.142*** (0.226)	1.136*** (0.222)
$\ln(1 + \text{Firm Age})$	-0.018** (0.008)	-0.017* (0.008)	-0.063 (0.066)	-0.060 (0.064)	-0.263 (0.165)	-0.280 (0.176)
Tobin's Q	-0.003*** (0.000)	-0.003*** (0.000)	0.003 (0.008)	0.003 (0.008)	0.090*** (0.019)	0.092*** (0.019)
$\ln(1 + \text{No. of Patents})$	-0.009 (0.010)		0.036 (0.044)		0.462* (0.230)	
$\ln(1 + \text{No. of Citations})$		0.024 (0.481)		3.519 (3.730)		6.633 (4.897)
Observations	719	719	629	629	860	860
Adjusted R-squared	0.001	0.0001	0.049	0.052	0.320	0.313
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

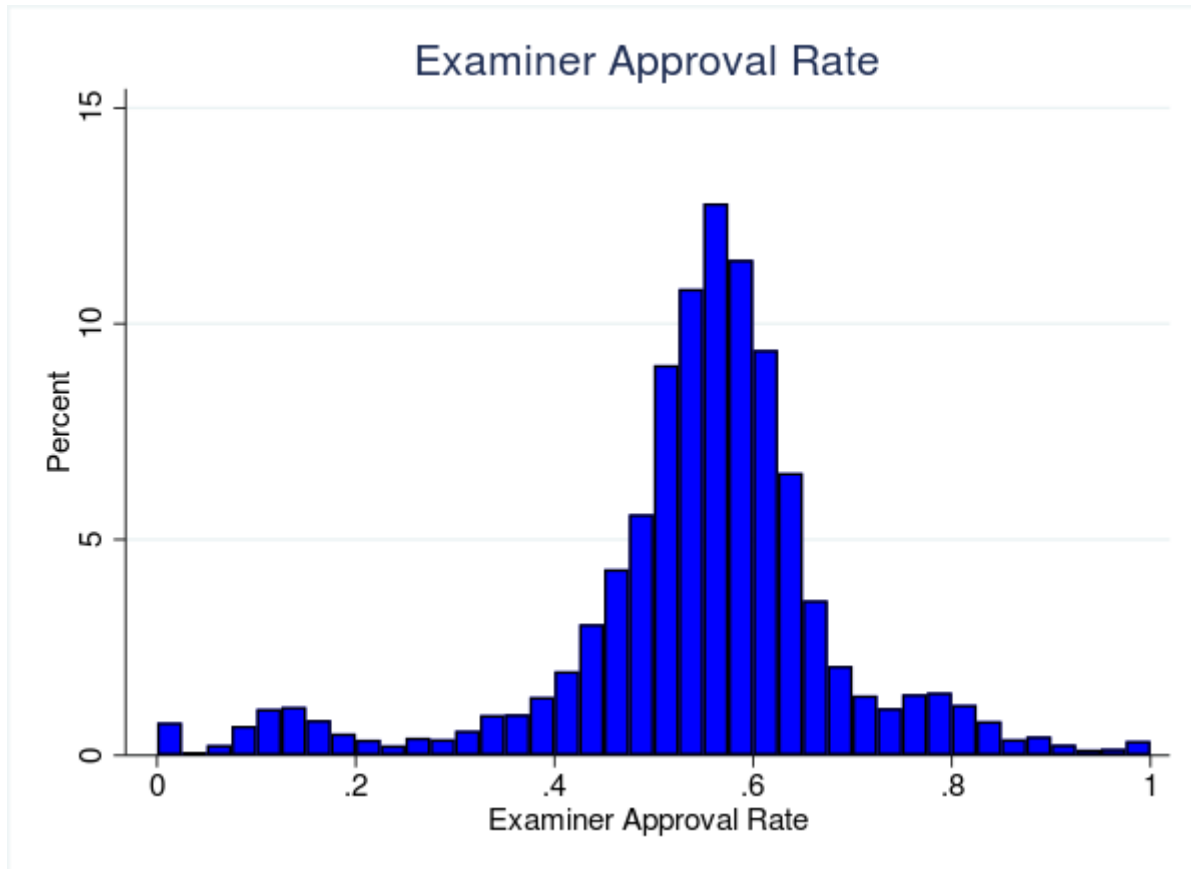
**Table 12: Instrumental Variable Analysis of the Relation between Trademarks and Information Asymmetry Facing the Firm**

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  $\ln(1 + \text{No. of Trademarks})$  on *Examiner Leniency* (the instrumental variable),  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(1 + \text{Firm Age})$ , *Tobin's Q*, *No. of Trademark applications*, and  $\ln(1 + \text{No. of Patents})$ . In the second stage regression, we use *Predicted  $\ln(1 + \text{No. of Trademarks})$*  as the main independent variable. *Forecast Error* is the mean-squared error of analysts' earnings forecasts. 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.  $\ln(1 + \text{No. of Trademarks})$  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  $\ln(1 + \text{No. of Trademarks})$*  is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter reputation rankings, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(1 + \text{Firm Age})$  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 ratio of market and book value of assets 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.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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	First Stage		(1)		(2)		(3)		(4)		(5)		(6)	
	Ln(1+ No. of Trademarks)	Second Stage	Forecast Error		Second Stage		Dispersion		Second Stage		No. of Analysts		Second Stage	
Examiner Leniency	1.501*** (0.254)		-0.245** (0.098)		-0.250** (0.097)		-0.614 (0.907)		-0.423 (0.840)		1.331 (1.920)		1.608 (1.982)	
Predicted Ln(1 + No. of Trademarks)														
Ln(Underwriter Reputation)	0.016 (0.048)		-0.021 (0.018)		-0.020 (0.018)		-0.124** (0.050)		-0.109* (0.054)		0.034 (0.369)		0.066 (0.365)	
Ln(Assets)	0.068*** (0.023)		0.033** (0.014)		0.033** (0.014)		0.102 (0.091)		0.085 (0.112)		1.206*** (0.329)		1.178*** (0.305)	
Ln(1 + Firm Age)	0.059 (0.047)		-0.000 (0.022)		0.001 (0.023)		-0.110 (0.079)		-0.131 (0.096)		-0.542*** (0.186)		-0.552** (0.198)	
Tobin's Q	0.004 (0.003)		-0.002 (0.001)		-0.002 (0.001)		-0.005 (0.005)		-0.004 (0.005)		0.074** (0.030)		0.075** (0.030)	
No. of Trademark Applications	0.028*** (0.002)		0.005** (0.002)		0.005** (0.002)		0.014 (0.028)		0.009 (0.030)		0.001 (0.043)		-0.001 (0.045)	
Ln(1 + No. of Patents)	0.020 (0.016)		0.001 (0.015)				0.056 (0.076)				0.366 (0.276)			
Ln(1 + No. of Citations)					0.447 (0.871)				6.085 (5.437)				5.761 (5.324)	
Observations	438		438		438		382		375		530		530	
F Statistic from 1st Stage	34.874													
Adjusted R-squared	0.308													
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 annual trademark examiner approval rates, defined as in equation (1). The sample consists of all trademark applications available at USPTO website from 1982 to 2015. We only consider examiners who have reviewed minimum 10 applications in a year.



# Online Appendix for “Trademarks in Entrepreneurial Firm Success: Empirical Evidence from Venture Backed Private Firms and Initial Public Offerings” (Not To Be Published)

## A.1: A test of the validity of our Instrumental Variable

In this section, we present the result supporting the validity of our instrumental variable, which is the leniency of trademark application examiners. As described in detail in Section 6.2 in the main text of our paper, we use a measure of trademark examiners’ leniency as an instrument for the number of trademarks granted to a firm. We compute yearly measures of examiners’ leniency. For our instrument to be valid, it should not be affected by trademark applicant firms’ characteristics and their investor characteristics. In Table A1, we test our instrument’s validity by regressing average examiner leniency, our instrument, on a set of firm (trademark applicant) characteristics, lead VC investor characteristics, and investment characteristics. Our objective is to show that examiner leniency is uncorrelated to the above characteristics. We estimate the following model:

$$Examiner\ Leniency_{it} = \alpha_0 + X_{it} + \epsilon_{it}, \quad (1)$$

where *Examiner Leniency* is the average leniency of examiners across all trademark applications filed by the firm  $i$  in the prior two year period.  $X$  represents a set of firm, investor, or investment characteristics. Our sample consists of all VC-backed private firms filing at least one trademark application in the prior two year period before their exit or failure to exit. We control for firm-specific characteristics: the number of patents (or citations on patents) held by a firm from five years prior to receiving the first round of VC-investment to the year of receiving the first round of VC-investment, and age of the firm at the time of receiving the first round of VC-investment. We also control for investor characteristics: age of the lead VC at the time of receiving the first round of VC investment. Lastly, we control for investment characteristics: total investment made in the firm by all VCs across all rounds and the number of rounds of VC investment (staging). We include fixed effects for industry, year, firm-headquarter state, and lead VC in our regressions and cluster standard errors at the lead VC level. In Table A1, our results show that firm or investor or

investment characteristics do not affect examiner leniency. This test provides some support for the notion that our instrument, namely, trademark examiner, leniency is valid.

## A.2: Propensity Score Matching Analysis

In this portion, 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 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.<sup>1</sup>

We assess the efficacy of our matched sample in Table A2. 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

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<sup>1</sup>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.



various regressions. Since in this subsample some control firms are matched with multiple treated 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.

### **A.2.1 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 A3. 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 valuation computed using first day closing price. We find that the coefficients of trademarks are positive and significant at the 5 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**.

### **A.2.2 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 A4. 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 1 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**.

### **A.2.3 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 A5. In Columns (1) and (8), the dependent variables are the operating performance in years 1, 2, 3, and 4 after IPO. We show that firms with higher number of trademarks are associated with higher level of post-IPO operating performance. The results are significant at 1 percent levels in Columns (1), (2), (3), (4), (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**.

### **A.2.4 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 A6. 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 10 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**.

## **A.3 The Relation between Trademarks and Propensity for Successful 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 a probit model. We have the same set of controls as our baseline linear probability regressions. We present the results of the above regressions in the Table A7. In Columns (1) and (2), we use IPO and acquisition dummy as the

dependent variable. We find that the coefficients of 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 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. 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**.

Next, we run a two-stage probit regression model 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 linear regressions. We also include an additional control, i.e., the number of applications (*Applications<sub>it</sub>*) in both stages, to control for the fact that a firm with more applications may be likely to have more registered trademarks. We report the results of these regressions in Table A8. In Column (1), we report the first-stage regression result of our IV analysis, which corresponds to successful exit through IPO or acquisitions (corresponding second stages shown in Columns (2) and (3)). 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 29.60 and the adjusted R-squared is 25.7 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. Corresponding first stage results for other two measures of successful exit (IPO only and M&A only) satisfy the relevance condition, but are suppressed in the table. 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. Thus, 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**.

## 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: Regression Analysis showing that Trademark Examiner Leniency is Uncorrelated to Firm, Investment, and Investor characteristics**

In this table, we report the OLS regression of regressing trademark examiners' leniency on firm, investor, and investment characteristics to show that our instrument, examiners' leniency, is unaffected by these characteristics. Our sample consists of all the trademark applications made by VC-backed private firms in our sample after receiving the first round of investment to their IPO or acquisition in case of an exit or up to five years from receiving the last round of VC investment, defined as *No Exit*. *Examiner Leniency*, is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to their exit or *No Exit*.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  is the natural logarithm of one plus the total adjusted number of forward citations received by these patents.  $\ln(1 + \text{Firm Age})$  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.  $\ln(\text{Total Investment})$  is the natural logarithm of the total VC investments across all rounds received by a private firm.  $\ln(1 + \text{VC Age})$  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. *No. of Rounds by VCs* is the total number of rounds of VC investments received by a private firm. Constant and fixed effects 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.

Variables	(1) Examiner Leniency	(2) Examiner Leniency
$\ln(1 + \text{No. of Patents})$	0.002 (0.003)	
$\ln(1 + \text{No. of Citations})$		0.092 (0.093)
$\ln(1 + \text{Firm Age})$	0.002 (0.003)	0.002 (0.003)
$\ln(\text{Total Investment})$	0.002 (0.002)	0.002 (0.002)
$\ln(1 + \text{VC Age})$	0.006 (0.009)	0.006 (0.009)
No. of Rounds by VCs	0.001 (0.001)	0.001 (0.001)
Observations	2,808	2,808
Adjusted R-squared	0.088	0.088
Industry FE	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes
Lead VC FE	Yes	Yes

**Table A2: Propensity Score Matching Diagnostic Tests**

This table reports the diagnostic tests of propensity score matching. Propensity score matching is implemented using the following covariates:  $\ln(1 + \text{No. of Patents})$ ,  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(1 + \text{Firm Age})$ ,  $\text{ROA}$ ,  $\text{Industry}$  dummy, and  $\text{Year}$  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.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter’s reputation ranking, obtained from Jay Ritter’s website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of firm to the year of IPO.  $\text{ROA}$  is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO.

<b>Panel A</b>		Pre-Match Sample Characteristics			
Variable	Mean		%bias	t-test	
	Treated	Control		t	p>t
$\ln(1 + \text{No. of Patents})$	0.865	0.506	41.000	6.100	0***
$\ln(\text{Underwriter Reputation})$	1.929	1.929	0.000	0.000	0.996
$\ln(\text{Assets})$	3.352	3.342	0.700	0.100	0.919
$\ln(1 + \text{Firm Age})$	2.038	1.852	25.600	3.980	0***
ROA	-0.097	-0.125	9.100	1.380	0.167

<b>Panel B</b>		Post-Match Sample Characteristics			
Variable	Mean		%bias	t-test	
	Treated	Control		t	p>t
$\ln(1 + \text{No. of Patents})$	0.865	0.849	1.800	0.260	0.792
$\ln(\text{Underwriter Reputation})$	1.929	1.940	-2.000	-0.340	0.734
$\ln(\text{Assets})$	3.352	3.288	4.100	0.690	0.491
$\ln(1 + \text{Firm Age})$	2.038	2.103	-8.900	-1.500	0.133
ROA	-0.097	-0.125	9.200	1.560	0.119

**Table A3: 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:  $\ln(1 + \text{No. of Patents})$ ,  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(1 + \text{Firm Age})$ ,  $\text{ROA}$ ,  $\text{Industry dummy}$ , and  $\text{Year dummy}$ .  $\text{IPO Valuation}$ ,  $\text{Secondary Valuation (FD)}$ , and  $\text{Secondary Valuation (FQ)}$  are the 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  $\text{IPO Valuation}$ , the first trading day closing price for  $\text{Secondary Valuation (FD)}$ , or the price at the end of first post-IPO fiscal quarter for  $\text{Secondary Valuation (FQ)}$ . 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.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter’s reputation ranking, obtained from Jay Ritter’s website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{IPO Proceeds})$  is the natural logarithm of IPO proceeds.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO.  $\text{ROA}$  is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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)	0.378*** (0.091)	0.386*** (0.089)	0.422** (0.175)	0.436** (0.166)	0.678*** (0.202)	0.691*** (0.203)
Ln(Underwriter Reputation)	-0.056 (0.140)	-0.053 (0.147)	-0.191 (0.200)	-0.195 (0.176)	-0.441 (0.269)	-0.398 (0.260)
Ln(Assets)	-0.460*** (0.098)	-0.461*** (0.100)	-1.013*** (0.243)	-1.016*** (0.242)	-1.020*** (0.255)	-1.016*** (0.260)
Ln(IPO Proceeds)	0.515*** (0.182)	0.525*** (0.175)	2.539*** (0.518)	2.557*** (0.517)	2.329*** (0.516)	2.336*** (0.528)
Ln(1 + Firm Age)	0.209 (0.185)	0.203 (0.177)	-0.203 (0.217)	-0.214 (0.199)	-0.605** (0.243)	-0.634** (0.249)
ROA	-1.748** (0.807)	-1.780** (0.835)	-1.883 (1.166)	-1.935 (1.199)	-1.498 (1.213)	-1.569 (1.266)
Ln(1 + No. of Patents)	0.073 (0.098)		0.096 (0.319)		0.358 (0.291)	
Ln(1 + No. of Citations)		-1.656 (4.665)		-5.194 (5.528)		4.644 (8.434)
Observations	967	967	997	997	1,048	1,048
Adjusted R-squared	0.136	0.136	0.226	0.226	0.235	0.234
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 A4: 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:  $\ln(1 + \text{No. of Patents})$ ,  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(1 + \text{Firm Age})$ ,  $\text{ROA}$ ,  $\text{Industry dummy}$ , and  $\text{Year dummy}$ .  $\ln(1 + \text{No. of Institutional Investors})$  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.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(\text{IPO Proceeds})$  is the natural logarithm of IPO proceeds.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO.  $\text{Underpricing}$  is the percentage difference between the first trading day closing price and the IPO offer price.  $\text{Tobin's } Q$  is ratio of market and book value of assets computed using the first trading day closing price.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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) Ln(1 + No. of Institutional Investors)	(2)
Ln(1 + No. of Trademarks)	0.095*** (0.032)	0.091*** (0.032)
Ln(Underwriter Reputation)	0.059 (0.061)	0.054 (0.064)
Ln(Assets)	0.022 (0.032)	0.023 (0.030)
Ln(IPO proceeds)	0.583*** (0.064)	0.586*** (0.067)
Ln(1 + Firm Age)	-0.091* (0.049)	-0.086 (0.053)
Underpricing	0.261*** (0.031)	0.257*** (0.030)
Tobin's Q	-0.014*** (0.004)	-0.014*** (0.004)
Ln(1 + No. of Patents)	-0.075** (0.036)	
Ln(1 + No. of Citations)		-1.493* (0.748)
Observations	801	801
Adjusted R-squared	0.572	0.569
Industry FE	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes

**Table A5: 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:  $\ln(1 + \text{No. of Patents})$ ,  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(1 + \text{Firm Age})$ ,  $\text{ROA}$ ,  $\text{Industry dummy}$ , and  $\text{Year dummy}$ . Dependent variable used in this table is  $\text{OIBDA}$  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.  $\text{OIBDA}$  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).  $\text{OIBDA}$  is adjusted for industry performance by subtracting contemporaneous industry (two-digit SIC code) medians.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website.  $\text{Tobin's } Q$  is ratio of market and book value of assets computed using the first trading day closing price.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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	OIBDA							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Year 1		Year 2		Year 3		Year 4	
Ln(1 + No. of Trademarks)	0.055*** (0.018)	0.056*** (0.017)	0.073*** (0.021)	0.069*** (0.021)	0.065 (0.068)	0.085 (0.071)	0.097*** (0.026)	0.087*** (0.027)
Ln(Assets)	0.075*** (0.018)	0.075*** (0.018)	0.066*** (0.011)	0.063*** (0.011)	0.124* (0.066)	0.132* (0.068)	0.055*** (0.013)	0.055*** (0.014)
Ln(1 + Firm Age)	0.019 (0.039)	0.018 (0.040)	0.071 (0.042)	0.094* (0.052)	0.415*** (0.142)	0.382** (0.141)	-0.007 (0.039)	0.038 (0.039)
Ln(Underwriter Reputation)	0.048** (0.022)	0.050** (0.024)	0.011 (0.033)	0.006 (0.035)	-0.062 (0.070)	-0.052 (0.068)	0.033 (0.039)	0.020 (0.037)
Tobin's Q	0.003 (0.002)	0.003 (0.002)	0.006* (0.003)	0.005 (0.003)	0.038*** (0.008)	0.040*** (0.010)	0.004*** (0.001)	0.003*** (0.001)
Ln(1 + No. of Patents)	0.015 (0.026)		-0.061** (0.027)		0.156** (0.065)		-0.071** (0.026)	
Ln(1 + No. of Citations)		0.376 (0.993)		0.178 (0.765)		3.476 (3.753)		-0.919 (1.868)
Observations	604	604	479	479	403	403	325	325
Adjusted R-squared	0.478	0.478	0.385	0.375	0.248	0.244	0.459	0.445
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 A6: 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:  $\ln(1 + \text{No. of Patents})$ ,  $\ln(\text{Underwriter Reputation})$ ,  $\ln(\text{Assets})$ ,  $\ln(1 + \text{Firm Age})$ ,  $\text{ROA}$ ,  $\text{Industry dummy}$ , and  $\text{year dummy}$ .  $\text{Forecast Error}$  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.  $\text{Dispersion}$  is the standard deviation of analysts’ earnings forecasts.  $\text{No. of Analysts}$  is the number of analysts following a firm at the end of the fiscal year of the IPO.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(\text{Underwriter Reputation})$  is the natural logarithm of the lead underwriter’s reputation rankings, obtained from Jay Ritter’s website.  $\ln(\text{Assets})$  is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO.  $\text{Tobin's } Q$  is ratio of market and book value of assets computed using the first trading day closing price.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  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)	(2)	(3)	(4)	(5)	(6)
	Forecast Error		Dispersion		No. of Analysts	
Ln(1 + No. of Trademarks)	-0.001 (0.012)	-0.002 (0.011)	-0.120* (0.062)	-0.123* (0.064)	0.343* (0.183)	0.358* (0.192)
Ln(Underwriter Reputation)	-0.007 (0.020)	-0.008 (0.020)	-0.047 (0.098)	-0.045 (0.098)	-0.035 (0.202)	0.005 (0.210)
Ln(Assets)	-0.008* (0.005)	-0.008* (0.004)	-0.053 (0.067)	-0.054 (0.067)	1.061*** (0.269)	1.054*** (0.264)
Ln(1 + Firm Age)	-0.010 (0.007)	-0.009 (0.007)	-0.086 (0.112)	-0.083 (0.113)	-0.267 (0.204)	-0.278 (0.206)
Tobin's Q	-0.003*** (0.001)	-0.003*** (0.001)	0.002 (0.007)	0.002 (0.007)	0.092*** (0.022)	0.094*** (0.021)
Ln(1 + No. of Patents)	-0.015 (0.009)		-0.023 (0.032)		0.328* (0.179)	
Ln(1 + No. of Citations)		-0.251 (0.339)		0.674 (1.445)		8.371* (4.138)
Observations	854	854	755	755	1,003	1,003
Adjusted R-squared	0.053	0.051	0.235	0.235	0.362	0.359
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 A7: 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. The coefficients depict marginal effects of respective variables. 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.  $\ln(1 + \text{No. of Trademarks})$  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.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from the founding year of a firm to the year of exit.  $\ln(\text{Total Investment})$  is the natural logarithm of the total VC investments across all rounds received by a private firm.  $\ln(1 + \text{VC Age})$  is the natural logarithm of one plus the number of years from the founding year of the lead VC to the year of exit.  $\ln(\text{VC Fund Size})$  is the natural logarithm of fund size of the lead VC in the year of the private firm's exit.  $\text{No. of Rounds by VCs}$  is the total number of rounds of VC investments received by a private firm.  $\text{Average No. of VCs per Round}$  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.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant and fixed effects 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.

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

**Table A8: Instrumental Variable Analysis of the Relation between Trademarks and the Propensity for Successful Exit (Probit)**

This table reports the instrumental variable regression (probit) results of successful exits of VC-backed firms on trademarks. In the first stage regression, we regress  $\ln(1 + \text{No. of Trademarks})$  on *Examiner Leniency* (the instrumental variable),  $\ln(1 + \text{Firm Age})$ ,  $\ln(\text{Total Investment})$ ,  $\ln(1 + \text{VC Age})$ ,  $\ln(\text{VC Fund Size})$ , *No. of Rounds by VCs*, *Average No. of VCs per Round*, *No. of Trademark applications*, and  $\ln(1 + \text{No. of Patents})$ . In the second stage regression, we use *Predicted  $\ln(1 + \text{No. of Trademarks})$*  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 prior two-year window.  $\ln(1 + \text{No. of Trademarks})$  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  $\ln(1 + \text{No. of Trademarks})$*  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.  $\ln(1 + \text{Firm Age})$  is the natural logarithm of one plus the number of years from firm founding year to the year of exit.  $\ln(\text{Total Investment})$  is the natural logarithm of the total VC investments across all rounds received by a private firm.  $\ln(1 + \text{VC Age})$  is the natural logarithm of one plus the number of years from lead VC founding year to the year of exit.  $\ln(\text{VC Fund Size})$  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.  $\ln(1 + \text{No. of Patents})$  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.  $\ln(1 + \text{No. of Citations})$  is the natural logarithm of one plus the total adjusted number of forward citations received by the patents. Constant and fixed effects 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*** (0.168)	1.625*** (0.169)	0.164 (0.866)	0.238 (0.852)	1.371*** (0.267)	1.363*** (0.265)
Ln(1 + Firm Age)	0.062*** (0.020)	-0.163*** (0.058)	-0.169*** (0.058)	0.054 (0.085)	0.063 (0.085)	0.158*** (0.053)	0.167*** (0.052)
Ln(Total Investment)	-0.017 (0.014)	0.123*** (0.040)	0.113*** (0.040)	0.256*** (0.053)	0.274*** (0.053)	0.040 (0.032)	0.024 (0.032)
Ln(1 + VC Age)	0.028 (0.060)	-0.312 (0.211)	-0.303 (0.212)	-0.083 (0.258)	-0.090 (0.256)	-0.307** (0.153)	-0.301* (0.154)
Ln(VC Fund Size)	0.112*** (0.024)	-1.153*** (0.246)	-1.165*** (0.245)	0.574*** (0.113)	0.542*** (0.112)	0.245*** (0.061)	0.268*** (0.061)
No. of Rounds by VCs	-0.008 (0.006)	0.039** (0.018)	0.038** (0.018)	0.032 (0.020)	0.036* (0.020)	0.003 (0.014)	-0.000 (0.014)
Average No. of VCs per Round	0.001 (0.009)	0.015 (0.028)	0.014 (0.028)	0.069** (0.031)	0.068** (0.031)	-0.036 (0.024)	-0.036 (0.024)
No. of Trademark Applications	0.036*** (0.005)	-0.052*** (0.011)	-0.053*** (0.011)	0.017 (0.030)	0.016 (0.030)	0.059*** (0.010)	0.060*** (0.010)
Ln(1 + No. of Patents)	0.008 (0.017)	-0.071 (0.053)		0.231*** (0.063)		0.167*** (0.053)	
Ln(1 + No. of Citations)			0.935 (2.240)		3.082 (2.331)		-1.262 (1.908)
Observations	2,214	2,214	2,214	2,129	2,129	2,480	2,480
F Statistic from 1st Stage	29.60						
Adjusted R-squared	0.257						
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
Lead FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes