Original Article

Trademarks and Entrepreneurial Firm Success: Theory and Evidence from Venture Capital Investments in Private Firms

Entrepreneurship Theory and Practice
2025, Vol. 49(3) 846–882

DOI: 10.1177/10422587241300438
journals.sagepub.com/home/etp
Sage

Onur Bayar[1], Thomas J. Chemmanur[2], Harshit Rajaiya[3], Xuan Tian[4], and Qianqian Yu[5]

Abstract

We theoretically model an entrepreneur's choice of his firm's products to trademark, the relation between the number of trademarks and venture capital (VC) investment staging, long-run operating performance, and successful firm exit probability. We test model predictions using a large dataset of trademarks registered by VC-backed private US firms. We find that firms with a larger number of trademarks at first VC investment have a smaller number of VC financing rounds; have larger long-run sales and employment; and have greater probabilities of successful exit (initial public offering [IPO] or acquisition). Our instrumental variable analysis demonstrates that more trademarks causally enhance firm performance and reduce VC staging.

JEL code: G23, G24, L26, O34

Keywords

trademarks, venture capital staging, long-run sales, long-run employment, private firm exit

Introduction

Trademarks are an important determinant of the economic value created by firms. A trademark is a word, symbol, or other signifier used to distinguish a good or service

[1]Alvarez College of Business, University of Texas at San Antonio, San Antonio, TX, USA
[2]Finance Department, Carroll School of Management, Boston College, MA, USA
[3]Telfer School of Management, University of Ottawa, Ottawa, ON, Canada
[4]PBC School of Finance, Tsinghua University, Beijing, China
[5]Perella Department of Finance, College of Business, Lehigh University, Bethlehem, PA, USA

Corresponding Author:
Thomas J. Chemmanur, Finance Department, Carroll School of Management, Boston College, Fulton Hall 336, Chestnut Hill, MA 02467, USA.
Email: chemmanu@bc.edu

produced by one firm from the goods or services of other firms (see, e.g., Landes & Posner, 1987). Firms use trademarks to differentiate their products from those of other firms, to reduce search costs for consumers, and to generate consumer loyalty through advertising, all of which may affect their product market performance (see, e.g., Economides, 1988) and therefore their financial performance. However, despite the importance of trademarks for the economic activities of firms, there is only a small academic literature on the role of trademarks in entrepreneurial finance.[1] This paper aims to contribute to this literature by analyzing, theoretically and empirically, the effect of trademarks on the staging of venture capital (VC) investments in private firms, on the long-run sales and long-run employment of these firms, and on the propensity of these firms to have a successful exit (IPO or acquisition) for the first time in the literature.

We first develop a theoretical model that allows us to address several interesting research questions regarding the role of trademarks in helping entrepreneurial firms succeed. First, how do entrepreneurial firms select which of their products to trademark? It is worth noting here that only a small fraction of the VC-backed start-up firms have trademarks. Second, do trademarks convey information to venture capitalists, IPO market investors, and potential acquirers about the number of high-quality products developed by a firm, and if so, how does this affect the staging of VC investment in these firms? Third, how do trademarks held by private firms affect the operating performance of these firms: in particular, what is the effect of trademarks on their sales and employment? Fourth, how do trademarks affect the probability of successful exit by private firms? We will use the new insights generated from our theoretical analysis in conjunction with those from the existing literature to develop testable hypotheses for our empirical analysis.

In our model, a firm has multiple products, each of which may be of high or low quality. The entrepreneur has private information about the quality of his firm's products, whereas outside investors (VCs or IPO market investors or potential acquirers) only know the probability distribution of the quality of each of the firm's products. The entrepreneur aims to sell a fraction of his shares to outside investors to raise financing for investment in the firm or to diversify his portfolio. The entrepreneur decides whether or not to trademark each of his firm's products based on the following trade-off: trademarking a product requires the entrepreneur to incur a significant cost (per product) but has the advantage of increasing the product's cash flow.[2] We assume that the cash flow benefit from trademarking is higher for higher-quality products. We show that, in the most plausible Perfect Bayesian Equilibrium (PBE) of this game, the entrepreneur trademarks all of the firm's high-quality products but does not trademark his firm's low-quality products. In this equilibrium, outside investors infer that firms will only trademark their higher-quality products so that trademarks convey information about the quality of the firm's products (and therefore intrinsic firm value) to outside investors. Our model also predicts that outsiders' assessment of the intrinsic value of a firm is increasing in the number of trademarks registered by the firm. It also predicts that the future cash flows of the firm will increase in the number of trademarks held by the firm at the time of the first VC investment. Finally, we extend our basic model to develop a model of VC staging that provides a relationship between trademarks and VC staging. The underlying intuition here is that VCs trade-off potential wastage of a fraction of their funding amount by startups (due to the agency costs of free cash flow, in the spirit of Jensen, 1986) versus re-contracting costs associated with each funding round to minimize the total cost. Our model predicts that, in equilibrium, the number of VC investment rounds in a firm will decrease in the number of trademarks held by the firm.

Based on the predictions of our theoretical model and insights from the existing entrepreneurship literature, we generate several testable hypotheses. First, VCs will spread their total investment in a firm with a larger number of trademarks over a smaller number of financing rounds (i.e., there will be a smaller extent of staging of VC investment into the firm so that a larger fraction of total investment will be provided in the first round). Second, we expect VC-backed private firms with a larger number of trademarks to have greater long-run sales. Third, we expect VC-backed private firms with a larger number of trademarks to have greater long-run employment. Fourth, we expect VC-backed private firms with a larger number of trademarks to have a greater probability of a successful exit (either through an IPO or an acquisition).

We test these hypotheses empirically using a large dataset of trademarks registered by VC-backed private firms, data on their sales and employment, and data on their exit decisions (IPOs or acquisitions). The results of our baseline empirical analyses may be summarized as follows. First, VC-backed private firms with a larger number of trademarks are associated with a lower extent of staging by VCs. A one standard deviation increase in the number of trademarks is associated with an average increase of 11.2% in the fraction of investment in round 1. 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. Second, VC-backed private firms with a larger number of trademarks are associated with greater long-run sales. A one standard deviation increase in the number of trademarks is associated with an average increase of 43.3% in the sales of a startup in the third year after receiving the first round of VC investment. Third, VC-backed private firms with a larger number of trademarks are associated with greater long-run employment. A one standard deviation increase in the number of trademarks is associated with an average increase of 31.3% in the employment of a startup in the third year after receiving the first round of VC investment. Fourth, VC-backed private firms with a larger number of trademarks have a greater chance of a successful exit. A one standard deviation increase in the number of trademarks is associated with an average increase of 7.6% in the probability of successful exit, where a successful exit is either through an IPO or an acquisition. It is also important to note that, in all our empirical tests, we control for the number of patents held by a firm and the number of citations to these patents.[3]

It may be argued that the relationships that we have established so far using our baseline analysis between a larger number of trademarks and various private firm characteristics are endogenous. For example, a higher-quality private firm (i.e., a firm with a higher-quality product portfolio) may apply for and receive a larger number of trademarks so that the relationships that we documented above between the number of trademarks and the sales or employment of startups or the probability of successful private firm exits may potentially be the result of higher firm (product) quality rather than the result of trademarks held by the firm causally enhancing firm performance (for a given product quality): indeed, our theoretical model suggests that firms are more likely to trademark higher-quality products. To examine whether trademarks causally lead to improved performance of VC-backed private firms and reduced VC staging, we conduct an instrumental variable (IV) analysis. We instrument for the number of trademarks registered by a firm using a measure of trademark examiner leniency. Trademark applications are randomly assigned to examining attorneys (examiners), who have significant discretion in the examination process. This exogenous variation in examiner leniency may affect the outcome of applications that 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 2 years prior to the first round of VC investment. The results of our IV analysis establish that a larger number of trademarks held by a firm causally leads to a lower extent of VC staging. We also establish that a larger number of trademarks held by VC-backed private firms causally leads to greater long-run sales and employment. Finally, we show that a larger number of trademarks held by a firm causally leads to a greater chance of successful exit (IPO or acquisition). In sum, our IV analyses allow us to conclude that the positive relationship we documented in our baseline analyses between the number of trademarks held by a firm and firm performance and the negative relationship between the number of trademarks and VC staging is causal.

Taken together, our theoretical model and empirical analysis provide support for two important roles that trademarks play in driving the success of private firms. First, the number of trademarks held by a private firm conveys (potentially noisy) information to venture capitalists, IPO market investors, potential acquirers, and other outsiders about its intrinsic value and future performance. Thus, VCs may use the number of trademarks held by a private firm at the time of the first VC investment to assess its intrinsic value and form a staging plan (i.e., how many financing rounds to split their total investment into). Since firms with a larger number of positive net present value (NPV) projects (and those with projects with a higher aggregate NPV) are less likely to waste the VC investment amount (and given that staging is costly due to recontracting costs), our theoretical model suggests that VCs will spread their total investment amount over a smaller number of financing rounds for firms with a larger number of trademarks. The results of our empirical analysis confirm that this is indeed the case in practice. Second, our theoretical model suggests that trademarks enhance private firm operating performance. Our empirical analysis finds that a larger number of trademarks at first VC investment causally leads to greater sales and larger employment in the third, fourth, and fifth years after VC investment, confirming that this is indeed the case in practice. Finally, our finding that the number of trademarks held by a firm causally leads to a greater probability of successful exit (through IPOs or acquisitions) provides additional support for both the informational and performance-enhancing roles of trademarks. This is because IPO market investors (in the case of IPOs) and potential acquirers (in the case of acquisitions) are likely to take into account both the recent performance of a private firm and its predicted future performance (as predicted by the trademarks it has registered) when deciding whether or not to invest in the equity of the firm at the time of exit.

The rest of the paper is organized as follows. Section "Relationship to the Existing Literature and Contribution" discusses the relationship of our paper to the existing literature and highlights our contribution to this literature. Section "Theoretical Model and Testable Hypotheses" presents our formal theoretical model and develops testable hypotheses for our empirical tests. Section "Data and Sample Selection" describes our data and sample selection procedures. Section "Empirical Analyses and Results" presents our empirical tests and results on the effect of trademarks on VC staging, their long-term sales and employment, and their propensity for successful exits. Section "Discussion and Conclusion" discusses the implications of our paper for theory and practice and concludes. Supplemental Appendix A provides detailed definitions of key variables used in our empirical analyses. Supplemental Appendix B presents the proofs of the two propositions in our theoretical model, discusses the institutional details of trademark applications and related costs, and presents additional robustness tests and empirical results.

Relationship to the Existing Literature and Contribution

Our paper is closely related to the literature studying the role of trademarks on the valuation of private firms by VCs and on the valuation of VC-backed IPOs. Block et al. (2014) show that the number and breadth of trademarks have an inverted U-shaped relationship with the valuation of startups by VCs. Zhou et al. (2016) show that patents and trademarks not only have a direct effect on the amount of VC financing but also have complementary positive effects. In contrast to the above papers focusing on VC valuation or VC funding, our focus is to study the effect of trademarks on VC staging, long-run sales and employment, and on successful exits of VC-backed private firms while controlling for the effect of patents. Thus, our paper generates important implications for fundamentally different outcome variables other than VC valuation or VC funding.[4] Furthermore, we also provide causal evidence on the effect of trademarks on VC staging, on long-run sales and employment, and the likelihood of successful exits of VC-backed private firms, for the first time in the literature. To the best of our knowledge, this is the first paper in the literature to study, either theoretically or empirically, the effect of trademarks on various outcomes of VC-backed private firms (other than valuation) through various stages in a private firm's life cycle, thus making an important contribution to the entrepreneurial finance literature.

In a contemporaneous paper, Fisch et al. (2022) use European data to show that trademark breadth is positively associated with IPO valuation and post-IPO stock returns. They argue that trademarks have real-option value since trademark breadth increases flexibility for firms, which generates additional value for firms from the trademarks when the option is exercised. In contrast to the above paper, we do not focus here on the effect of trademarks on IPO valuation or post-IPO performance. Rather, our focus is on the effect of trademarks on various outcomes in the life cycle of VC-backed startups. We rely on two economic channels through which trademarks benefit firms: signaling intrinsic firm value to outsiders and the performance-enhancing effect. We study the effect of trademarks on VC-staging, on the performance (sales and employment) of VC-backed private firms in the United States, and the likelihood of successful exit of such startups: all of these results are new to the literature.

Our paper is also related to the literature that studies the motivation of firms to file trademarks or not. Using a survey of a small sample of firms in creative and cultural industries, Castaldi (2018) shows that firms trademark their products or services to strengthen and protect their brands. They also show that firms may not trademark their products or services if they rely primarily on copyrights or if they are not even aware of trademarks. Using survey data on a sample of UK firms, Athreye and Fassio (2021) argue that firms may not trademark their products or services if they collaborate with their clients or rely on their distribution channels. Using a survey of 600 small and medium-sized enterprises (SMEs), Block et al. (2015) investigate the reasons for filing of trademarks by firms and find that SMEs file trademarks for marketing to their customers, protection of their intellectual properties, or to signal their innovativeness to investors. Uzuegbunam et al. (2019) show that corporate VC investment in firms leads to a lower number of trademark filings. In contrast to the above papers, we show in our theoretical model that firms may not trademark their products if the costs associated with trademarking exceed the benefits of trademarking, which is likely to be the case for lower-quality products. However, we acknowledge that the factors highlighted in the papers discussed above may also play an important role in private firms' decisions to trademark their products or services or not.

Our paper is also distantly related to the literature studying the effect of trademarks on established (seasoned) firms.[5] Sandner and Block (2011) show that trademarks have a positive effect on the valuation of public firms using Tobin's Q as a measure of market valuation. Faurel et al. (2016) use a sample of publicly traded (S&P 1500) firms to analyze the relationship between CEO incentives and the number of trademarks created by firms. Hsu et al. (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.[6]

Finally, our paper is indirectly related to the theoretical and empirical literature on IPOs and the exit decisions of private firms: see, for example, Chemmanur and Fulghieri (1999), Ferreira et al. (2014), Sherman and Titman (2002), and Spiegel and Tookes (2020) for the theoretical literature and see, for example, Chemmanur et al. (2009) for the empirical literature.[7] Schwienbacher (2008) develops a theoretical model analyzing how the level of innovation of a venture-backed private firm affects its exit decision, taking into account the financial contracting between the venture capitalist and the entrepreneur.

Theoretical Model and Testable Hypotheses

In this section, we first develop a theoretical model of trademarks. In Section "A Theoretical Model of Trademarks," we present our basic model analyzing how entrepreneurs decide which products to trademark (and which not to trademark); how trademarks improve firm performance; and the inferences drawn by venture capitalists and other investors about intrinsic firm value after observing the number of trademarks held by a firm. In Section "Extended Model: Trademarks Held by Private Firms and the Staging of Investments by Venture Capitalists," we extend our basic model to analyze the relation between the number of trademarks held by a firm and the staging of investment into the firm by VCs, that is, VCs' choice of the number of rounds over which to distribute their investments. We then develop testable hypotheses for our empirical tests based on the predictions of the above model in Section "Testable Hypotheses."

A Theoretical Model of Trademarks

There are two dates in the model: times 0 and 1. At time 0, the entrepreneur of a private firm sells a fraction α of his firm's equity to outside investors (venture capitalists or IPO market investors) and retains the remaining fraction $(1-\alpha)$ until time 1, where $0<\alpha<1$.[8] The total number of shares outstanding in the firm is normalized to 1 so that α can be thought of as either the fraction of shares or the number of shares sold by insiders at time 0.

The firm has a portfolio of N products. The quality of the firm's any given product i ($i = 1, \ldots, N$) is either high (H) or low (L), and at time 0, this is observable only to firm insiders, with $H > L$. We let $q_i = 1$ if the quality of the product i is H and $q_i = 0$ if the quality of the product i is L.[9] Outside investors do not observe the quality of any product i at time 0 but have a prior probability assessment that the quality of the product i is H with probability θ (and it is L with the complementary probability $(1-\theta)$), where $0<\theta<1$.[10] The type t of the firm is equal to the number of its high-quality (type H) products, that is, $t = \sum_{i=1}^{N} q_i$. A type t firm has t high-quality products and $(N-t)$ low-quality products. Thus, the firm can be one of $(N+1)$ types: $t \in \{0, 1, \ldots, N\}$. For example, if all of the N products of the firm are of high quality (H), the firm's type t is equal to N. On the other hand, if none of the firm's N products is of high quality, the firm's type t is equal to 0. If

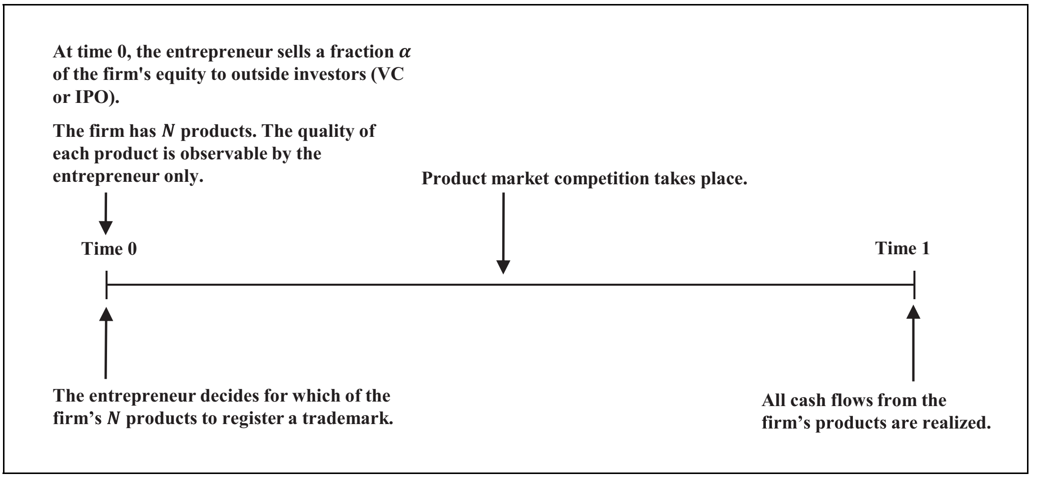

Figure 1. Sequence of events.

the firm has n number of high-quality products between the above two extremes, that is, $0<n<N$, the firm's type is given by n.[11]

In the absence of trademarks, the firm's expected time-1 cash flow from a type H product is X_H and the firm's expected time-1 cash flow from a type L product is X_L, where $X_H>X_L\geqslant 0$. The firm's fixed cost of registering a trademark for any product i at time 0 is $C>0$. We assume that if a product i is trademarked, this increases the firm's expected time-1 cash flow from product i by a certain multiplicative factor. In particular, we assume that if the firm registers a trademark for a product i that is of type H, the firm's expected time-1 cash flow from this product is $k_H X_H$. Similarly, if the firm registers a trademark for a product i that is of type L, the firm's expected time-1 cash flow from this product is $k_L X_L$, where $k_H>k_L\geqslant 1$. For tractability, we normalize k_L to 1 and k_H to $k>1$.[12] This means that the benefit of trademarking a product is greater for a high-quality (H) product than it is for a low-quality (L) product.[13] Outside investors (VCs or IPO market investors or potential acquirers) observe the number of trademarks held by a firm.

At time 1, the cash flows from the firm's N products are realized and become observable to all market participants. There is a risk-free asset in the economy, the net return on which is normalized to 0. All agents are assumed to be risk-neutral. The sequence of events is given in Figure 1.

At time 0, outsiders face asymmetric information about the intrinsic value of the firm.[14] This is because the intrinsic value of the firm is a function of the quality of the product portfolio of the firm, which is unobservable to outsiders. In the absence of any trademarks as signals of unobservable product quality, outsiders' expected time-1 cash flow from any product i is $\theta X_H + (1-\theta)X_L$: that is, they calculate this cash flow based on their prior probability assessment of the quality of each product. Therefore, in this case, the outsiders' valuation of the firm at time 0 would be given by:

$$V_0^u = N(\theta X_H + (1-\theta)X_L). \tag{1}$$

Given the setting above, the objective of a type t firm's entrepreneur is to maximize his expected payoff at time 0:

$$\max_{a} \; E[W(t,a)] = \alpha\left(X_0(a) - \sum_{i=1}^{N} a_i C\right) + (1-\alpha)\left(X(t,a) - \sum_{i=1}^{N} a_i C\right) \tag{2}$$

where

$$X(t,a) = \sum_{i=1}^{N} (q_i(ka_i + (1-a_i))X_H + (1-q_i)X_L), \tag{3}$$

and $a = (a_1, \ldots, a_N)$ denotes the entrepreneur's choice vector of which products to trademark so that $a_i \in \{0,1\}$ for all $i = 1, \ldots, N$. In the above objective function, the first term gives the cash flow received by the entrepreneur by selling a fraction of α of his equity of the firm; hence, $X_0(a)$ denotes the outside investors' time-0 valuation of the firm's expected time-1 cash flow as a function of the firm's choice of its products to trademark, a.

The second term in the entrepreneur's objective gives his time-0 expected value of his firm's time-1 cash flow, denoted by $X(t,a)$, of which fraction $(1-\alpha)$ is received by the entrepreneur due to his residual equity holding $(1-\alpha)$ in the firm. $X(t,a)$ is a function of the firm's type, t, and the firm's choice of trademarks, a. The number of the firm's trademarks is denoted by m, where $m = \sum_{i=1}^{N} a_i$. The following proposition characterizes the properties of the equilibrium in our model of trademarks. We focus only on the pure strategy separating PBE of this model.

Proposition 1. (The Equilibrium of the Basic Trademark Model) Let $\alpha(kX_H - X_L) < C < \alpha(kX_H - X_L) + (1-\alpha)(k-1)X_H$. Then, there exists a separating PBE in which:[15]

(i) At time 0, a type t firm registers a trademark for each of its t high – quality products and it registers no trademarks for any of its $(N-t)$ low – quality products. That is, for $i = 1, \ldots, N$, the firm's equilibrium trademarking strategy is characterized as follows:

$$a_i^* = \begin{cases} 1 & \text{if } q_i = 1, \\ 0 & \text{if } q_i = 0. \end{cases} \tag{4}$$

The number of the firm's trademarks is $m^* = \sum_{i=1}^{N} a_i^* = \sum_{i=1}^{N} q_i = t$. Outside investors' posterior belief is that a product with a registered trademark is of high quality with probability 1 and a product with no registered trademark is of low quality with probability 1: that is, $P(q_i = 1 | a_i^* = 1) = 1$ and $P(q_i = 0 | a_i^* = 0) = 1$ for $i = 1, \ldots, N$. Furthermore, $P\left[t = \sum_{i=1}^{N} a_i^* | a^*\right] = 1$.

(ii) The outsiders' valuation $V_0(a^*)$ of the firm at time 0 is equal to its intrinsic value $V_0(t)$, which is given by

$$V_0(a^*) = V_0(t) = tkX_H + (N-t)X_L - tC. \tag{5}$$

(iii) The outsiders' valuation of the firm at time 0 (given in Equation 5) is strictly increasing in the number of its registered trademarks, m^*.

(iv) The expected time-1 total cash flow of the firm is strictly increasing in the number of its registered trademarks, m^*.

The above proposition (parts (i) and (ii)) shows that the equilibrium strategy of a type t firm is to register a trademark for all of its high-quality products but none for its low-quality products. Thus, the number of the firm's trademarks in equilibrium is equal to the number of its high-quality products: that is, $m^* = t$. This means that, in the above separating equilibrium, the type t of the firm is fully revealed to outside investors through its optimal trademarking strategy so that the outsiders' valuation $V_0(a^*)$ of the firm in equilibrium is equal to its intrinsic value $V_0(t)$, which is equal to the firm's total expected cash flow net of the firm's total trademark costs as a function of the firm's type t and its type-dependent equilibrium trademarking strategy $a^*(t)$. Thus, in equilibrium:

$$V_0(t) = X(t, a^*(t)) - \sum_{i=1}^{N} a_i^* C = tkX_H + (N - t)X_L - tC, \tag{6}$$

where

$$X(t, a^*(t)) = tkX_H + (N - t)X_L, \ \sum_{i=1}^{N} a_i^* C = tC. \tag{7}$$

Given the separating equilibrium strategy $a^*(t)$ of each firm type t about its trademarked products, outside investors have no uncertainty about the firm type: that is, $P\left[t = \sum_{i=1}^{N} a_i^* | a^*\right] = 1$. This means that, in the equilibrium of our model, the firm can credibly convey valuable information about its type (the quality of its product portfolio) to outside investors using its trademarking strategy.[16]

Thus, in addition to increasing the cash flow from the sale of a product in the product market, trademarks also serve as accurate signals of unobservable intrinsic firm value. That is, in a fully separating equilibrium with trademarks, outsiders can distinguish a firm with a larger number of high-quality products from a firm with a smaller number of high-quality products, thereby inferring the intrinsic value of the firm from the number of trademarks held by the firm. Consequently, a firm with a higher-quality product portfolio (i.e., a firm with a greater value of $t \in \{0, 1, \ldots, N\}$) can convey information to outside investors about the unobservable quality of its product portfolio by using trademarks as costly signals.

For the above separating equilibrium (with trademarks as signals of firm type t) to exist, the following upward incentive compatibility (IC) constraints have to be satisfied for any firm of type t, where $t = 0, 1, \ldots, (N - 1)$:

$$\begin{aligned}(tkX_H + (N - t)X_L) - tC \geqslant \; & \alpha((t + 1)kX_H + (N - t - 1)X_L) \\ & + (1 - \alpha)(tkX_H + (N - t)X_L) - (t + 1)C,\end{aligned} \tag{8}$$

which is equivalent to $C \geqslant \alpha(kX_H - X_L)$. The above upward IC constraints in Equation 8 imply that a type t firm has no incentive to deviate from its equilibrium strategy by registering a trademark for any of its low-quality (type L) products, thereby mimicking other firm types with a greater number of high-quality products. Thus, it is not cost-effective for a firm to acquire extra trademarks for any of its low-quality products and thereby fool outside investors into paying a higher price for the firm's equity at time 0. Recall that the entrepreneur keeps a residual equity holding $(1-\alpha)$ in the firm and therefore still holds a substantial claim to the firm's cash flow at time 1. Since the time-1 cash flow benefit of trademarking in the product market is much smaller for a low-quality (L) product than it is for a high-quality (H) product (i.e., $k_L = 1 < k_H = k$), it does not pay for the firm to trademark any of its low-quality products at cost C in the equilibrium of our model.

Furthermore, in the above separating equilibrium, the following downward IC constraints have to be satisfied for any firm of type t, where $t = 1, \ldots, N$:

$$\begin{aligned}(tkX_H + (N-t)X_L) - tC \geqslant \alpha((t-1)kX_H + (N-t+1)X_L) \\ + (1-\alpha)((t-1)kX_H + X_H + (N-t)X_L) - (t-1)C,\end{aligned} \tag{9}$$

which is equivalent to $C \leqslant \alpha(kX_H - X_L) + (1-\alpha)(k-1)X_H$. The above downward IC constraints in Equation 9 imply that a type t firm has no incentive to deviate from its equilibrium strategy by not registering a trademark for any of its high-quality (type H) products and thereby mimicking other firm types with a smaller number of high-quality products. A key necessary condition for the above separating equilibrium is $k>1$: that is, the performance-enhancing role of a trademark in the product market is greater for a high-quality (type H) product than it is for a lower-quality (type L) product.

According to part (iii) of Proposition (1), our model predicts that the outsiders' valuation of the firm increases with the number of trademarks held by the firm at the time of investment. This prediction suggests that an important economic role that trademarks play in the life of young firms is in conveying information about intrinsic value and future financial performance to investors. In other words, trademarks may act as a credible signal to private investors such as VCs, IPO market investors, and potential acquirers, 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 high-quality product line (associated with that trademark).[17] Therefore, assuming that it is costly to acquire and maintain trademarks, a firm's trademark portfolio is likely to serve as a credible signal of intrinsic firm value to outsiders such as VCs, IPO market investors, and potential acquirers, over and above any publicly available information conveyed by the firm's patent portfolio.[18] We will refer to this role of trademarks as their "informational" role.

Finally, part (iv) of the above proposition shows that the expected future (time 1) cash flow of the firm also increases with the number of trademarks held by the firm at the time of investment. Thus, our model predicts that firms with a larger number of trademarks will perform better in the product market and will therefore have better accounting or operating performance (e.g., sales). This is consistent with the direct effect of trademarks on the future financial performance of a private firm, which we refer to as the "performance-enhancing" role of trademarks.[19]

Extended Model: Trademarks Held by Private Firms and the Staging of Investments by Venture Capitalists

In this subsection, we extend our basic model presented in Section "A Theoretical Model of Trademarks" to theoretically analyze how the number of trademarks held by a private firm will affect the staging of funds invested by VCs into a private firm. We assume that the equilibrium prevailing in this section is the separating equilibrium characterized in Proposition 1. In other words, a venture capitalist observing the number of trademarks held by a firm can infer the number of high-quality products held by the private firm (the two numbers are the same in the equilibrium characterized in Proposition 1).[20] Suppose that the syndicate of VCs investing in a private firm expects that the total investment requirement of the private firm is I over the VCs' total investment period. We normalize the length of the VCs' total investment period in the private firm to 1.[21] For tractability, we assume that the total amount of funds I will be disbursed by VCs to the private firm in equal installments over M investment rounds, each of which is spaced in equal time intervals (i.e., of length $1/M$) from one another over the entire VC investment period.[22] The total number of stages, M^*, will be optimally chosen by VCs in equilibrium and will be characterized in Proposition 2.

Due to costly and imperfect monitoring of the private firm by VCs, a fraction $\kappa > 0$ of the disbursed VC funds will be wasted by the private firm during the time period from the corresponding financing round until the end of the VCs' investment period. We use the word "wasted" in a broad sense for a collection of negative NPV activities, such as perquisite consumption; paying excess salary to the firm's entrepreneurial founder and other employees; or investing in negative NPV projects from which the entrepreneur may enjoy private benefits. Thus, if the financing round investment amount I/M is distributed by VCs to the private firm in stage j, where $j = 1, \ldots, M$, the amount of funds wasted by the private firm equals $\kappa \frac{(M-j+1)}{M} \frac{I}{M}$.[23] We assume that the fraction κ of VC funds wasted by the private firm is strictly decreasing in the total NPV of the projects available to the firm.[24] Since high-quality products (when viewed as projects to be invested in) have higher NPV than low-quality products, and trademarking increases product cash flows, this means that κ is decreasing in the number of high-quality products developed by the firm (which, as we saw in Proposition 1, is the same as the number of trademarks held by the firm).

For a given total number of financing rounds, M, the total amount of investment funds wasted by the private firm during the VCs' total investment period is given by:

$$\sum_{j=1}^{M} \kappa \frac{(M-j+1)}{M} \frac{I}{M} = \kappa I \frac{(M+1)}{2M}. \tag{10}$$

One should note from Equation 10 that the total amount of VC funds wasted by the private firm is decreasing in the number of financing rounds, M.[25] However, the staging of VC funds over several number of financing rounds also involves additional contracting costs for VCs: let us denote the contracting cost per each VC financing round by F. Therefore, the VCs will select the optimal number of stages, M^*, to minimize the following total cost of VC staging, which is given by:

$$\min_{M \geqslant 1} \; MF + \kappa I \frac{(M+1)}{2M}. \tag{11}$$

Proposition 2. (The Equilibrium Number of VC Financing Rounds in the Extended Trademark Model) The equilibrium number of VC financing rounds is given by:

$$M^* = \left\lfloor \sqrt{\kappa \frac{I}{2F}} + 0.5 \right\rfloor. \tag{12}$$

Furthermore, the equilibrium number of VC financing rounds of a private firm (given in Equation 12) is strictly decreasing in the number t of trademarks held by the firm.

In the equilibrium of our model, VCs choose the optimal number of financing rounds over which to disburse the total investment amount they plan to invest in the firm based on the following trade-off. On the one hand, increasing the total number of financing rounds has two benefits: first, by reducing the amount disbursed per round and second, by reducing the length of time the investment amount stays in the firm, together reducing the total amount wasted by the firm over the lifetime of VC investment in the firm. However, given that there is a recontracting cost F associated with each financing round, as the number of VC investment rounds becomes larger, the total contracting cost becomes prohibitively large. Given that the fraction of the total VC investment amount wasted declines with the number of trademarked (high quality) products (which have higher NPVs than low-quality products), the equilibrium number of financing rounds emerging from the above trade-off will decrease in the number of trademarked products held by the firm.

Testable Hypotheses

Our model generates a number of predictions that will serve as testable hypotheses for our empirical analysis. We present these hypotheses in chronological order (i.e., following the life cycle of a VC-backed firm).

We first analyze the relation between the number of trademarks registered by a firm and the extent of the staging of VC investment (i.e., the number of rounds the total VC investment in the firm is split up into). First, Proposition 1 predicts that a private firm with a larger number of trademarks registered to it will be perceived by VCs as having a higher intrinsic value. Furthermore, Proposition 2 predicts that the number of stages of VC investment in a private firm will be negatively related to the number of trademarks held by the firm. Finally, given the smaller number of financing rounds that the 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 total VC investment to be made in the very first VC investment round (*H1*).

We next analyze the relation between the number of trademarks held by a firm and its post-VC investment operating performance. Part (iv) of Proposition 1 predicts that the future cash flows of a firm will be increasing in the number of trademarks held by it. We test this prediction using two measures. First, we expect the long-run post-investment sales of a private firm to increase in the number of trademarks held by the firm (*H2*). Second, since firms with greater cash flows are likely to hire a larger number of employees, we expect the long-run post-investment employment of a private firm to increase in the number of trademarks held by the firm (*H3*).

Finally, we analyze the relation between the number of trademarks held by a firm and its propensity for successful exit. Part (iii) of Proposition 1 predicts that private firms with a larger number of trademarks will be perceived as having higher intrinsic value by outside investors (such as venture capitalists, IPO market investors, and potential acquirers). Part (iv) of Proposition 1 predicts that outside investors will also expect firms with a larger number of trademarks to have better future operating performance. Therefore, these two results imply that private firms with a larger number of trademarks will have a higher probability of successful exit through an IPO or an acquisition by another firm (*H4*).

It should be noted that the predictions of our model are not conceptually inconsistent with a causal interpretation and with the setting of our IV analysis. In our theoretical model, our focus is only on a firm's decision to apply for trademarks or not: in equilibrium, all trademark applications are granted, as long as the firm pays the cost of applying and maintaining its trademarks. This is because we have not incorporated the trademark examination process into our formal theoretical model. However, to empirically evaluate whether trademarks causally improve firm performance, we exploit the random variation across trademark examiners in their rate of granting trademarks. In other words, since, in practice, even some high-quality products may be denied trademarks by less lenient trademark examiners (as we explain in more detail in Section "Instrumental Variable: Average Examiner Leniency"), we can use trademark examiner leniency as an instrument in our IV analysis to establish the causal effect of trademarks.

To see why there is no conceptual inconsistency between our formal model predictions and the setting of our IV analyses, consider a modified setting where we explicitly incorporate the trademarking examination process into the setting of our model. Here the entrepreneur is aware that some of his trademark applications will be rejected with a certain probability during the trademark examination process, where this rejection probability is unrelated to product quality (the application will be granted with the complementary probability). While this will introduce some additional complexity to the entrepreneur's objective given in Equation 2, the nature of the equilibrium will remain qualitatively unchanged from that given in Proposition 1, with the private firm applying to trademark all its high-quality products and not applying to trademark its low-quality products. Outside investors will also continue to infer that firms with a greater number of trademarks are of higher intrinsic value (on average), even though they realize that some of the private firms' trademark applications might have been denied.[26]

Our results in Proposition 2 on the relation between the number of trademarks held by a private firm and the number of VC financing rounds will also continue to hold (qualitatively) in such a more complex setting. This means that our testable hypothesis *H1* will remain the same as before but with a causal interpretation. Thus, the number of trademarks held by the firm at the time of the first VC investment will causally reduce the number of financing rounds. This is because VCs realize that, in this modified setting, trademarking increases the cash flows (and therefore NPVs) from high-quality products so that the fraction of firm cash flow wasted will be lower for firms with a larger number of trademarks, thereby causally reducing the number of financing rounds over which the VC's total amount of investment is split up into.

Furthermore, hypotheses *H2* and *H3* will go through with a causal interpretation as well. In other words, we expect the number of trademarks to causally increase the long-run sales and long-run employment of private firms. Finally, since outsiders such as IPO market investors and potential acquirers are aware that trademarks will causally improve firm performance in this slightly modified setting, the number of trademarks held by a private firm will causally increase the probability of successful exit through an IPO or acquisition (so that hypothesis *H4* can be given a causal interpretation as well with no inconsistency with our theoretical model).

Data and Sample Selection

Sample Selection

We obtained data on VC-backed private firms in the United States from Thomson One VentureXpert.[27] 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 observe all IPOs and acquisitions till 2015 to consider all exits within 5 years of the last round of VC investment. 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 United States. We identify lead VC investors for each entrepreneurial firm following Nahata (2008) and use VentureXpert to extract their respective ages and fund sizes. After dropping observations with missing data on lead VC or other relevant firm characteristics, we are left with a sample of 13,593 VC-backed private firms. We further drop observations with missing data on the first round of VC investment. This leaves us with 12,903 unique startups. We obtain the trademark data from the USPTO website. We use the USPTO website to obtain the patent data. We obtain data on employment and sales for entrepreneurial firms from the National Establishment Time Series (NETS), which is a longitudinal database provided by Dun & Bradstreet and is widely used in research on private firms.[28]

Measures of Trademarks

We obtain the list of all the trademark applications available in the USPTO database (USPTO trademark case file dataset) from 1985 to 2010.[29] This includes all the applications whether they were granted (i.e., registered trademarks), pending, or abandoned (an application that is no longer pending and thus cannot mature into registration). Similar to the patent literature, we consider abandoned trademark applications as rejected. The case files of trademark applications 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 the identifier and adopt a similar matching technique to the one used in the NBER Patent Project.

For any firm, we count the number of trademarks it has registered from 5 years prior to receiving the first round of VC investment to the year of receiving the first round of VC investment. Our theoretical model suggests that we should look at all trademarks within a fixed time frame before the first VC investment in the firm. This is because, in our theoretical model, the entrepreneur's private information is about only one underlying variable, namely, the number of high-quality products of the firm, which are trademarked in equilibrium. Furthermore, this private information is not evolving over time. We choose 5 years for comparability across firms: doing so ensures that we are measuring trademarks over the same horizon for all firms in our sample.[30] We consider trademarks registered before the first round of VC investment since they reflect the quality of startups before the involvement of VCs. In other words, VCs are unlikely to be involved in the development of products or brands that were trademarked prior to the first round of VC investment.

Following Faurel et al. (2016), we use the registration year of trademarks for constructing our measure of trademarks. We use a logged measure (Ln (1 + No. of Trademarks)) to capture the value of trademarks for a particular firm. We take the natural logarithm because the distribution of trademarks is skewed. We add one to the actual values to avoid losing observations with zero trademarks.

Measures of Innovation

We control for the quantity and quality of a firm's innovation output in our regressions, as measured by the number of patents and that of patent citations, respectively. We obtain patent and citation data from the USPTO website and match it to the VentureXpert dataset. We also adjust our measures of patents and citations following the existing literature (see Hall et al., 2001; Seru, 2014 for more details about truncation).

We construct two measures of innovation. The first measure, Ln (1 + No. of Patents), is the natural logarithm of one plus the total number of class-adjusted patents for a particular firm from 5 years prior to receiving the first round of VC investment to the year of receiving the first round of VC investment. The second measure, Ln (1 + No. of Citations), is the natural logarithm of one plus the total number of class-adjusted forward citations received by all the patents used in constructing the patent count 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.

Measures of Long-run Sales and Employment

We use the NETS data to construct long-run sales and employment of startups. We obtain non-missing information on sales and employment for startups in our sample by matching it to the NETS database. Specifically, we measure the raw sales (in millions of US dollars) and employment of startups (in thousands) in the third, fourth, and fifth years, respectively, after the first round of VC investment. We also measure industry-adjusted sales by scaling the sales of a startup by the average number of sales of startups in the same two-digit SIC code in the same year. We measure industry-adjusted employment using a similar approach.

Summary Statistics

We report the summary statistics of our sample in Table 1.[31] Panel A shows that an average firm in our sample receives nearly half (49.9%) of the total VC funding in the first round and typically receives three rounds of VC investments. Furthermore, an average firm typically has two VC investors investing in the first round. Around 16.1% of firms have at least one trademark in the 5 years before receiving the first round of VC investment, while 16.5% of firms have at least one patent, and 4.1% of firms have both patent(s) and trademark(s). About 30.6% of firms in our sample have filed a trademark application in the 2-year window prior to receiving the first round of VC investment. We show the sales and employment information of 8,722 and 8,723 startups, respectively, in Panel A. The sales and employment for the rest of the startups in our sample are missing.

In Panel B, we present the summary statistics of the eventual exits of VC-backed private firms. Out of 12,903 private firms in our sample, 4,346 (33.68%) had a successful exit through acquisition, 1,380 (10.7%) had a successful exit through IPO, and the rest did not have an exit.[32]

Lastly, in Panel C, we present the summary statistics of trademark applications and registered trademarks for firms at the time of exit. We compute a yearly measure of examiner leniency or the percentage of applications approved by them. The average examiner approval rate is around 54%. Figure B1 in Supplemental Appendix B depicts the distribution of this variable, which exhibits significant variation across different examiners' approval rates. We compute the average examiner leniency faced by firms by averaging the examiner leniency across all trademark applications of firms in the 2-year period before receiving the first round of VC investment. We also measure the number of trademark applications filed and registered by a firm in a 2-year period before receiving the first round of VC investment. An average firm files around three trademark applications in the 2-year period before receiving the first round of VC investment.

Table 1. Summary Statistics for VC-Backed Private Firms.

Panel A: Summary statistics at the time of the first round of investment in private firms

Variables	*N*	Mean	Std. Dev.	Min	Max
Fraction of investment in Round 1	12,903	0.499	0.391	0	1
No. of rounds by VCs	12,903	3.539	2.681	1	23
Raw sales (Year 3)	8,722	14.0508	124.9965	0.0007	7370.425
Industry adjusted sales (Year 3)	8,722	1.1632	4.8475	0.0003	223.0042
Raw employment (Year 3)	8,723	0.088	0.569	0.001	32.889
Industry-adjusted employment (Year 3)	8,723	1.162	4.883	0.001	339.221
Ln (Total Investment)	12,903	2.489	1.495	−6.908	5.250
No. of trademarks	12,903	0.480	2.099	0	104
Ln (1 + Patents)	12,903	0.106	0.287	0	1.486
Ln (1 + Citations)	12,903	0.001	0.003	0	0.0241
Ln (1 + Firm Age)	12,903	1.625	0.823	0	4.060
Syndicate size	12,903	2.736	2.081	1	10
Ln (1 + VC Age)	12,903	2.562	0.777	0	4.234
Ln (VC Fund Size)	12,903	6.302	1.773	1.609	10.087

Panel B: Exit status of VC-backed private firms

Status	*N*	Percent
Acquisition	4,346	33.68
Went public	1,380	10.7
Write-off	7,177	55.62
Total	12,903	100

Panel C: Summary statistics of examiner leniency and trademark applications

Variables	*N*	Mean	Std. Dev.	Min	Max
Examiner leniency (annual)	3,948	0.530	0.069	0.192	0.909
Number of trademarks	3,948	1.624	2.246	0	35
Number of trademark applications	3,948	3.112	3.890	1	88

Note. This table reports summary statistics for the sample of VC-backed private firms in the United States between 1990 and 2010 (ordinary least square sample) as well as the subsample of VC-backed startups that applied for trademark applications within 2 years prior to the first round of VC investment in these startups (IV sample). All variables are winsorized at the 1st and 99th percentiles except for the number of trademarks and trademark applications. Panel A reports summary statistics for VC-backed private firms at the time of receiving their first round of investment from VCs. Panel B reports the eventual exit status of the firms within 5 years of receiving their last round of VC investment. *Write-off* is a case defined for a firm if it is neither acquired nor had an IPO within 5 years of the last round of VC investment. Panel C reports summary statistics of examiner leniency and trademark applications made by VC-backed startups. These startups have applied for trademark applications within 2 years prior to receiving the first round of VC investment. All other variables are defined in detail in the next few tables.
IV = instrumental variable; VC = venture capital.

Empirical Analyses and Results

Methodology and Identification

We empirically test the relation between the number of trademarks of a startup and staging of VC investment in the startup, long-run sales and employment of the startup, and the likelihood of successful exit of the startup. We first use ordinary least squares (OLS) regressions to establish a baseline relationship between trademarks and the above-mentioned firm outcomes. However, it may be argued that the relations established using our baseline analyses linking the number of trademarks and various private firm characteristics are the result of endogeneity: in particular, our theoretical model suggests that firms are more likely to trademark higher-quality products so that the relationship between the number of trademarks held by a firm and its future performance (long-run sales and employment and higher probability of successful exit) may be the result of a "product quality effect." On the other hand, it is also possible that trademarks also causally enhance firm performance, that is, for a given quality of its product portfolio, a larger number of trademarked products enhance firm performance (on average). To establish a causal relationship between the number of trademarks held by a firm and firm performance, we conduct IV analyses. In this IV analysis, we make use of the random assignment of trademark applications to trademark examining attorneys and the exogenous source of variation in attorney leniency in approving trademark applications. Our IV analysis approach builds on similar applications in the innovation literature.[33] We describe the construction of our instrument in detail in the next subsection.

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 detail in Section B2 in Supplemental Appendix B, the USPTO stated 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 is permissible by federal law. A generic or merely descriptive mark will be rejected and so will be a mark that can create a "likelihood of confusion" with an existing trademark.[34] 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. In the setting of our theoretical model, firms will only trademark their high-quality products. 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 the examiner.[35] 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 the leniency of trademark examiners (randomly assigned) that affects the outcome of trademark applications. Furthermore, the leniency of the examiner is unlikely to be correlated with firm quality.[36] We then compute a time-varying measure of the leniency of each 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:

$$\text{Individual Examiner Leniency}_{ijkt} = \frac{\text{Grants}_{jt} - \text{Grant}_k}{\text{Applications}_{jt} - 1}, \tag{13}$$

where Grants_{jt} and Applications_{jt} are the numbers of trademarks granted and applications reviewed, respectively, by examiner j in the same application year as application k.[37] 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., Melero et al., 2020).

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 2-year window prior to receiving its first round of VC investment. We consider trademark applications filed before the first round of VC investment since such applications are unlikely to be driven by VCs. We choose a 2-year window to analyze the number of trademark applications made by a firm since an application on average takes around 2 years (600 days) before it is either accepted or abandoned. We do this to ensure that our instrument does not capture any resubmission of a rejected trademark application after suitable modifications. Furthermore, looking at the fixed 2-year window prior to the exit ensures that we analyze the effect of trademark applications filed for the same duration for all firms in our sample.[38] We then compute the average examiner leniency for a firm over the 2-year window as the instrument for the number of trademarks registered by the firm. Specifically, we compute our instrument, that is, the average examiner leniency (Avg Leniency$_{it}$) for a firm i in year t, as follows:

$$\text{Avg Leniency}_{it} = \frac{1}{n_i}\sum_{j} \text{Individual Examiner Leniency}_{ijkt}, \tag{14}$$

where j indexes trademark examiner and n_i is the total number of trademark applications filed by firm i in the 2-year window.

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

$$\text{Ln}(1 + \text{No. of Trademarks})_{it} = \alpha_1 \text{Avg Leniency}_{it} + \alpha_2 \text{ Applications}_{it} + \alpha_3 X_{it} + \epsilon_{it}. \tag{15}$$

$$\text{Outcome}_{it} = \beta_1 \widehat{\text{Ln}(1 + \text{No. of Trademarks})_{it}} + \beta_2 \text{ Applications}_{it} + \beta_3 X_{it} + \epsilon_{it}. \tag{16}$$

In the first-stage regression (Equation 15), we regress Ln (1 + No. of Trademarks)$_{it}$ on the instrument (Avg Leniency$_{it}$), that is, the average examiner leniency computed for firm i.[39] Ln (1 + No. of Trademarks)$_{it}$ is defined as the natural logarithm of one plus the total number of trademarks granted to a firm in the 2-year window. Applications$_{it}$ is the number of trademark applications filed in the 2-year window and X_{it} is a vector of controls used in prior tests. Equation 16 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.[40]

Relevance Condition. Figure B1 in Supplemental Appendix B shows the distribution of examiners' yearly approval rates (as defined in Equation 13), 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 2-year window, as reported in all the first-stage regression results of our IV analysis. In all these first-stage regressions, we find that the coefficients of the instrument are positive and highly significant at the 1% level. We report the Kleibergen-Paap rk Wald F statistics in the first stage of all IV regressions. The F-statistics in these first-stage regressions exceed the critical value of 10 (Stock & Yogo, 2002). These results suggest that our instrument satisfies the relevance condition required for a valid instrument.

Exclusion Restriction. To satisfy the exclusion restriction, our IV should affect the outcome variables only through its relation with the endogenous variable, that is, the number of trademarks registered by a firm in the 2-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, that is, 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 trademark applications are randomly assigned to examiners, irrespective of the quality of an application.

We also conducted a validity test and show in Table B1 of Supplemental Appendix B that our instrument is uncorrelated with many observable firm characteristics. Furthermore, 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, it cannot take actions that may affect the outcome variables in the period between the assignment of an application to an examiner and the outcome of the application. Therefore, trademark examiner leniency is unlikely to affect firm outcomes except through the first-stage channel, that is, by affecting the number of trademarks granted to firms. In summary, our instrument satisfies the second condition required to satisfy the exclusion restriction as well.

The Effect of the Number of Trademarks on VC Staging: Baseline and IV Analyses

We study the relation between the number of trademarks and the staging of VC investments in startups (corresponding to *H1*). We first estimate the following OLS model:

$$\mathrm{Var}_{it} = \alpha_0 + \alpha_1 \mathrm{Ln}(1 + \text{No. of Trademarks})_{it} + X_{it} + \epsilon_{it}, \tag{17}$$

where i indexes firm and t indexes year. To study the relation between the number of trademarks and the staging of investments by VCs, we use two measures for the staging of VC investments as dependent variables. The first measure of staging is the *Fraction of Investment in Round 1*, defined as the VC investment in the first round divided by the total VC investment across all rounds in a private firm. The second measure of staging is *No. of Rounds by VCs*, defined as the total number of VC investment rounds in a firm. Our explanatory variable of interest is Ln (1 + No. of Trademarks).

X represents a vector of control variables. In particular, we include both class-adjusted patents (Ln (1 + No. Patents)) and citations (Ln (1 + 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 (Ln (1 + Firm Age)), the number of VC investors in the first round (*Syndicate Size*), the age of the lead VC (Ln (1 + VC Age)), and the fund size of the lead VC (Ln (VC Fund Size)). We include fixed effects for industry and state of firm headquarters 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 firms backed by the same lead VC.

We present our results of the above tests in Panel A of Table 2. In Column (1), we use the fraction of VC investment in the first round as the dependent variable. We find that the coefficients of the number of trademarks are positive and statistically significant at the 1% level. In Column (2), we use the number of rounds of VC investment as the dependent variable and find that coefficients of trademarks are negative and statistically significant at the 1% level. In economic terms, a one standard deviation increase in the number of trademarks is associated with an average increase of 11.2% increase in the first-round investment. Also, a one standard deviation increase in the number of trademarks is associated with a decrease of 0.37 rounds in terms of the staging of VC investment. In Table B2 in Supplemental Appendix B, we show that our results on VC staging are robust to measuring trademarks using an indicator variable, which takes the value of one if a startup has at least one trademark and otherwise zero. Thus, even on the extensive margin, trademarks are associated with a lower extent of VC staging. These results suggest that private firms with a larger number of trademarks are associated with a lower extent of staging of investments by VCs, thus supporting *H1*.

Next, we conduct our IV analysis using a two-stage least squares (2SLS) regression model (similar to the two-stage tests shown in Equations 15 and 16). We report the results of these regressions in Panel B of Table 2. The sample size for our IV analysis is smaller than that for our OLS analysis since it only contains firms that have made at least one trademark application in the 2-year window prior to their exits. As mentioned earlier, 30.6% of firms in our OLS sample have filed a trademark application in the 2-year window prior to their exits. In Column (1), we report the first-stage regression result of our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1% level. The first-stage F-statistic is 100.924 and the adjusted R-squared is 32.8%, suggesting that our instrument satisfies the relevance condition for a valid instrument. We report the second-stage regression results of the effect of trademarks on VC staging exits in Columns (2) and (3). We show that the number of trademarks causally leads to a higher fraction of VC investment in the first round and causally leads to a smaller number of investment rounds by VCs. Thus, our IV results also support *H1*.

The Effect of Trademarks on the Long-run Sales of Startups: Baseline and IV Analyses

We now study the relation between the number of trademarks and the long-run sales of startups, corresponding to our hypothesis *H2*. We measure raw and industry-adjusted sales in the third, fourth, and fifth years after the first round of VC investment in a startup. We present the results of the baseline analyses in Panel A of Table 3. We show that the number of trademarks is associated with a larger value of raw and industry-adjusted sales in the third, fourth, and fifth years after the first round of VC investment. All these results are significant at the 1% level. In economic terms, a one standard deviation increase in the number of trademarks is associated with an increase of 43.3% in the average sales of a startup in the third year after receiving the first round of VC investment.[41]

Next, we conduct our IV analysis using a 2SLS regression model. We report the results of these IV regressions in Panel B of Table 3. Our first stage (shown in Column (1)) results confirm that our instrument is relevant and significant. We show the second stage results in Columns (2) to (7). Our IV results demonstrate that trademarks causally lead to better long-run sales for startups, which supports our hypothesis *H2*. Our results are significant

Table 2. The Relation between the Number of Trademarks and the Staging of VC Investment: Baseline and IV Analysis.

Panel A: The relation between the number of trademarks and the staging of VC investment (baseline analysis)

	(1)	(2)
Variables	Fraction of investment in Round 1	No. of rounds by VCs
Ln (1 + No. of Trademarks)	0.116*** (0.007)	−0.767*** (0.045)
Ln (1 + No. of Patents)	0.020 (0.016)	−0.226** (0.103)
Ln (1 + No. of Citations)	−2.068 (1.354)	21.587** (9.008)
Ln (1 + Firm Age)	−0.115*** (0.007)	1.126*** (0.054)
Syndicate size	−0.051*** (0.002)	0.139*** (0.012)
Ln (1 + VC Age)	−0.075*** (0.008)	0.561*** (0.052)
Ln (VC Fund Size)	0.013*** (0.004)	−0.058** (0.028)
Observations	12,898	12,898
Adjusted *R*-squared	0.243	0.243
Industry FE	Yes	Yes
State FE	Yes	Yes

Panel B: The relation between the number of trademarks and the staging of VC investment (IV analysis)

	(1)	(2)	(3)
	First stage	Second stage	
Variables	Ln (1 + No. of Trademarks)	Fraction of investment in Round 1	No. of rounds by VCs
Examiner leniency	1.065*** (0.106)		
Ln (1 + No. of Trademarks)		0.336*** (0.088)	−1.852*** (0.571)
Ln (1 + No. of Patents)	0.097*** (0.031)	0.009 (0.029)	−0.097 (0.193)
Ln (1 + No. of Citations)	−7.091*** (2.606)	0.319 (2.128)	13.684 (14.850)
Ln (1 + Firm Age)	0.091*** (0.012)	−0.137*** (0.013)	1.324*** (0.085)
Syndicate size	−0.001 (0.004)	−0.050*** (0.003)	0.136*** (0.018)
Ln (1 + VC Age)	0.013 (0.012)	−0.076*** (0.012)	0.596*** (0.072)
Ln (VC Fund Size)	0.001 (0.005)	0.016** (0.006)	−0.124*** (0.034)

(continued)

Table 2. (continued)

Panel B: The relation between the number of trademarks and the staging of VC investment (IV analysis)

	(1)	(2)	(3)
	First stage	Second stage	
Variables	Ln (1 + No. of Trademarks)	Fraction of investment in Round 1	No. of rounds by VCs
No. of trademark applications	0.081*** (0.009)	−0.023*** (0.008)	0.110** (0.047)
Observations	3,938	3,938	3,938
F Statistic	100.924		
Adjusted *R*-squared	0.328		
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Note. This table reports the baseline and IV regression results of the effect of the number of trademarks on staging by VCs in Panel A and Panel B, respectively. The *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 (1 + No. of Trademarks) (in the OLS analysis sample) *is* the natural logarithm of one plus the total number of trademarks that a firm has registered in the 5-year period before the first round of VC investment. 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 5-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 patents of a firm filed in the 5-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 investors 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 the first round of lead VC investment at the private firm. Ln (VC Fund Size) is the natural logarithm of fund size (in millions of US dollars) of the lead VC at the time of the first round of VC investment in a private firm. Ln (1 + No. of Trademarks) (in the IV analysis sample) is the natural logarithm of one plus the total number of trademarks that a firm has registered in the 2-year window prior to the year of first-ever VC investment in a startup. *No. of Trademark Applications* (in the IV analysis sample) is the number of trademark applications made by a firm in the 2-year window prior to the year of IPO/acquisition or the year of write-off, which is defined as 5 years after the last VC investment in case of no successful exit by then. Constant (suppressed), two-digit SIC industry fixed effects, and state of a firm's headquarters 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% levels, respectively.
IV = instrumental variable; VC = venture capital; OLS = ordinary least squares.

Table 3. The Relation between the Number of Trademarks and Long-Run Sales of Startups: Baseline and IV Analyses.

Panel A: The relation between the number of trademarks and long-run sales of startups (baseline analysis)

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw sales			Adjusted sales		
Variables	Year 3	Year 4	Year 5	Year 3	Year 4	Year 5
Ln (1 + No. of Trademarks)	12.598*** (4.629)	15.388** (6.772)	14.276** (6.235)	0.607*** (0.109)	0.619***(0.112)	0.566*** (0.119)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,715	8,503	8,277	8,715	8,503	8,277
Adjusted *R*-squared	0.008	0.011	0.012	0.003	0.013	0.013
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: The relation between the number of trademarks and long-run sales of startups (IV analysis)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage	Second stage					
		Raw sales			Adjusted sales		
Variables	Ln (1 + No. of Trademarks)	Year 3	Year 4	Year 5	Year 3	Year 4	Year 5
Examiner leniency	0.666*** (0.109)						
Ln (1 + No. of Trademarks)		41.623 (25.526)	54.726* (29.258)	71.908** (34.610)	2.595* (1.379)	2.840** (1.355)	3.136** (1.405)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,932	2,932	2,832	2,740	2,932	2,832	2,740
F Statistic	37.238						
Adjusted *R*-squared	0.205						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table reports the OLS and IV regression results of the effect of the number of trademarks on the long-run sales of startups in Panel A and Panel B, respectively. *Raw Sales (Year 3, Year 4*, and *Year 5)* are the raw sales (in millions of US dollars) of a startup in the third, fourth, and fifth years, respectively, after the first round of VC investment in the startup. *Adjusted Sales (Year 3, Year 4*, and *Year 5)* are the ratio of raw sales of a startup in the third, fourth, and fifth year, respectively, after the first round of VC investment in the startup over the average two-digit SIC industry sales in the same year. Controls include Ln (1 + No. of Patents); Ln (1 + No. of Citations); Ln (1 + Firm Age); *Syndicate Size*; Ln (1 + VC Age); and Ln (VC Fund Size). In addition, we control for the *No. of Trademark Applications* in Panel B. All variables are defined in detail in Table 2. Constant (suppressed), two-digit SIC industry fixed effects, and state of a firm's headquarters 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% levels, respectively.
IV = instrumental variable; VC = venture capital; OLS = ordinary least squares.

at 5% or 10% levels.[42] Broadly, our IV analysis results suggest that trademarks causally improve long-run sales of VC-backed private firms, supporting the pure performance-enhancing role of trademarks.

The Effect of Trademarks on the Long-Run Employment of Startups: Baseline and IV Analyses

We now study the relation between the number of trademarks and the long-run employment of startups, corresponding to our hypothesis *H3*. We measure raw and industry-adjusted employment in the third, fourth, and fifth years after the first round of VC investment in a startup. We present the results of the baseline analyses in Panel A of Table 4. We show that more trademarks are associated with a greater value of raw and industry-adjusted employment in the third, fourth, and fifth years after the first round of VC investment. All these results are significant at the 1% level. In economic terms, a one standard deviation increase in the number of trademarks is associated with an increase of 31.3% in the average employment of a startup in the third year after receiving the first round of VC investment. Thus, our baseline results suggest that a larger number of registered trademarks of private firms is associated with enhanced long-run employment, which supports our hypothesis *H3*.[43]

Next, we conduct our IV analysis using a 2SLS regression model. We report the results of these IV regressions in Panel B of Table 4. Our first stage (shown in Column (1)) results confirm that our instrument is relevant and significant. We show the second stage results in Columns (2) to (7). Our IV results on raw employment are in the expected direction but are insignificant. However, our IV results show that trademarks causally lead to a greater long-run industry-adjusted employment for startups, which supports our hypothesis *H3*. Our IV results on industry-adjusted employment are significant at the 5% or 10% levels.[44] Taken together, our results suggest that trademarks causally improve the long-run employment of VC-backed private firms, again supporting a "pure performance enhancing role" of trademarks.

The Effect of Trademarks on Successful Private Firm Exit: Baseline and IV Analyses

Finally, we study the relation between the number of trademarks and the propensity for successful exit of VC-backed private firms, corresponding to our hypothesis *H4*, by first estimating the following linear probability model:

$$\text{Exit}_{it} = \alpha_0 + \alpha_1 \text{Ln}(1 + \text{No. of Trademarks})_{it} + X_{it} + \in_{it}, \tag{18}$$

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., Nahata, 2008). Therefore, our first measure is a dummy variable *IPO or M&A*, which is equal to 1 if a venture-backed private firm went public or was acquired within 5 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 5 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 5 years of the last round of VC investment and 0 otherwise. Similar to other baseline analyses, we measure the number of trademarks in the 5-year period prior to the first round of VC investment.

Table 4. The Relation between the Number of Trademarks and Long-Run Employment of Startups: Baseline and IV Analyses.

Panel A: The relation between the number of trademarks and long-run employment of startups (baseline analysis)

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw employment			Adjusted employment		
Variables	Year 3	Year 4	Year 5	Year 3	Year 4	Year 5
Ln (1 + No. of Trademarks)	0.057*** (0.017)	0.066*** (0.019)	0.065*** (0.019)	0.449*** (0.097)	0.524*** (0.127)	0.471*** (0.116)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,716	8,504	8,278	8,716	8,504	8,278
Adjusted *R*-squared	0.034	0.047	0.047	0.000	0.028	0.021
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: The relation between the number of trademarks and long-run employment of startups (IV analysis).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage	Second stage					
		Raw employment			Adjusted employment		
Variables	Ln (1 + No. of Trademarks)	Year 3	Year 4	Year 5	Year 3	Year 4	Year 5
Examiner leniency	0.665*** (0.109)						
Ln (1 + No. of Trademarks)		0.182 (0.170)	0.282 (0.187)	0.346 (0.220)	1.758 (1.273)	2.182* (1.232)	2.456** (1.243)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,933	2,933	2,833	2,741	2,933	2,833	2,741
F Statistic	37.1						
Adjusted *R*-squared	0.205						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table reports the OLS and IV regression results of the effect of the number of trademarks on the long-run employment of startups in Panel A and Panel B, respectively. *Raw Employment (Year 3, Year 4*, and *Year 5)* is the raw employment of a startup in the third, fourth, and fifth years, respectively, after the first round of VC investment in the startup. The raw employment numbers are reported in thousands. *Adjusted Employment (Year 3, Year 4*, and *Year 5)* is the ratio of raw employment of a startup in the third, fourth, and fifth years, respectively, after the first round of VC investment in the startup over the average two-digit SIC industry employment in the same year. Controls include Ln (1 + No. of Patents); Ln (1 + No. of Citations); Ln (1 + Firm Age); Syndicate Size; Ln (1 + VC Age); and Ln (VC Fund Size). In addition, we control for the *No. of Trademark Applications* in Panel B. All variables are defined in detail in Table 2. Constant (suppressed), two-digit SIC industry fixed effects, and state of a firm's headquarters 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% levels, respectively.
IV = instrumental variable; VC = venture capital; OLS = ordinary least squares.

We present our results of the baseline analyses in Panel A of Table 5. In Column (1), we use IPO or acquisition dummy as the dependent variable. We find that the coefficient of the number of trademarks is positive and significant at the 1% level. In Columns (2) and (3), we use the IPO dummy and acquisition dummy, respectively, as the dependent variable, the coefficient of the number of trademarks is positive and significant at the 1% level.[45] Our results are also economically significant: a one standard deviation increase in the number of trademarks is associated with an average increase of 7.6% in the probability of a successful exit through either IPO or M&A.[46] In Table B6 in Supplemental Appendix B, we show that our results are robust to using a logit regression instead of a linear regression.[47] These results suggest that firms with a larger number of trademarks are associated with a greater chance of successful exit, which supports our hypothesis *H4*.

Next, we conduct our IV analysis by running a two-stage linear probability regression model.[48] We report the results of these regressions in Panel B of Table 5. In Column (1), we report the first-stage regression result of our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1% level. The first-stage F-statistic is 112.034 and the adjusted R-squared is 32.9%, suggesting that our instrument satisfies the relevance condition for a valid instrument. We report the second-stage regression results of the effect of trademarks on private firms' successful exits in Columns (2) to (4). In Column (2), the dependent variable is a dummy variable for IPOs or acquisitions (*IPO or M&A*). We find that the coefficient of the number of trademarks is positive and significant at the 1% level. In Column (2), the dependent variable is a dummy variable for IPOs (*IPO only*). The coefficient of the number of trademarks is also positive and significant at the 1% level. Finally, in Column (3), the dependent variable is a dummy variable for acquisitions (*M&A only*). We find that the coefficient of the number of trademarks is negative but insignificant. 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, that is, trademarks have a pure performance-enhancing role, which supports our hypothesis *H4*.

Discussion and Conclusion

Summary of the Main Results

In this paper, we develop a theoretical model of trademarking by entrepreneurial firms. Our model generates predictions for the relation between the number of trademarks held by private firms and the staging of investment into these firms by VCs as well as for the relation between the number of trademarks held by firms and the future operating performance of these firms, and their propensity for successful exit. We test several hypotheses based on model predictions and the existing literature using a large dataset of trademarks registered by VC-backed private firms from 1985 to 2010. Our empirical analysis generates a number of novel findings consistent with the implications of our theoretical model. First, we find that entrepreneurial firms holding a larger number of trademarks experience a lower extent of staging of investment by VCs: VCs provide this investment over a smaller number of rounds and the fraction of total VC investment provided in the first round is increasing in the number of trademarks held by the firm. Second, VC-backed firms holding a larger number of trademarks experience greater long-run sales and greater long-run employment. Third, VC-backed firms holding a larger number of trademarks have a higher likelihood of achieving a successful exit through an IPO or an acquisition. We make use of an IV analysis to demonstrate that our baseline findings are causal, thus supporting a

Table 5. The Relation between the Number of Trademarks and the Propensity for Successful Exit: Baseline and IV Analyses.

Panel A: The relation between the number of trademarks and the propensity for successful exit (baseline analysis).

	(1)	(2)	(3)
Variables	IPO or M&A	IPO only	M&A only
Ln (1 + No. of Trademarks)	0.070*** (0.009)	0.027*** (0.007)	0.043*** (0.009)
Controls	Yes	Yes	Yes
Observations	12,898	12,898	12,898
Adjusted *R*-squared	0.141	0.068	0.082
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Panel B: The relation between the number of trademarks and the propensity for successful exit (IV analysis)

	(1)	(2)	(3)	(4)
	First stage	Second stage		
Variables	Ln (1 + No. of Trademarks)	IPO or M&A	IPO only	M&A only
Examiner leniency	1.121*** (0.106)			
Ln (1 + No. of Trademarks)		0.278*** (0.103)	0.402*** (0.070)	−0.124 (0.105)
Controls	Yes	Yes	Yes	Yes
Observations	3,938	3,938	3,938	3,938
F Statistic	112.034			
Adjusted *R*-squared	0.329			
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Note. This table reports the linear probability model (LPM) and IV regression results of successful exits of VC-backed firms on the number of trademarks in Panel A and Panel B, respectively. *IPO or M&A* is an indicator variable that takes the value equal to one if a private firm goes public or is acquired, and zero otherwise. *IPO only* is an indicator variable that takes the value equal to one if a private firm goes public, and zero otherwise. *M&A only* is an indicator variable that takes the value equal to one if a private firm is acquired, and zero otherwise. Controls include Ln (1 + No. of Patents); Ln (1 + No. of Citations); Ln (1 + Firm Age); Ln (Total Investment); Ln (1 + VC Age); *Avg Syndicate Size per Round; No. of Rounds by VCs; and* Ln (VC Fund Size). In addition, we control for the *No. of Trademark Applications* in Panel B. *Avg Syndicate Size per Round* is the total number of VC investors across all investment rounds in a startup divided by the number of investment rounds in the startup. Ln (Total Investment) is the natural logarithm of the total VC investments across all rounds received by a private firm (in millions of dollars). All other variables are defined in detail in Table 2. Constant (suppressed), two-digit SIC industry fixed effects and state of a firm's headquarters 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% levels, respectively.
IV = instrumental variable; VC = venture capital.

performance-enhancing role for trademarks: that is, the number of trademarks held by a VC-backed private firm causally leads to a smaller number of VC financing rounds, have causally better long-run operating performance (as measured by the long-run sales of the firm and long-run employment), and a higher propensity for successful exit through (IPOs or acquisitions).

Theoretical Implications

Our paper develops a number of novel insights on how entrepreneurial firms decide which of their products to obtain trademarks on (given that startup firms are notoriously financially constrained and obtaining and maintaining trademarks is costly) and how the number of trademarks held by a firm may affect the financing, valuation, and performance of such firms. The above insights from our theoretical analysis and empirical findings will help future researchers to formulate new theoretical models and empirical analyses of entrepreneurial firm financing and performance, taking into account how the trademarks registered by these firms can be expected to affect the staging of their financing from VCs, operating performance, and their likelihood of successful exit.

Our theoretical model demonstrates that entrepreneurs have more of an incentive to trademark higher-quality products while leaving lower-quality products without trademarks, given the (reasonable) assumption that the benefit of trademarking a product in terms of generating future sales and profits to the firm is likely to be greater for higher-quality products. This, in turn, implies that venture capitalists, IPO market investors, and potential acquirers are likely to be able to infer the quality of the firm's products (and hence overall firm value and future performance) from observing the number of trademarks held by the firm so that VCs stage their investment to a lower extent (smaller number of financing rounds) in such firms. Our theoretical model also implies that firms with a larger number of trademarks will have better operating performance as measured by their long-run sales and employment, and also a greater probability of successful exit (through IPOs or acquisitions).

Our research complements the findings of existing literature (discussed in detail in Section "Relationship to the Existing Literature and Contribution") in several important ways. First, it advances a new rationale for why firms trademark some products but not others (see, e.g., Castaldi, 2018 for an existing rationale) and also provides a new hypothesis regarding the benefits of trademarking (see, e.g., Fisch et al., 2022) who provide an alternative real-options argument for why firms benefit from trademarking). Second, while Block et al. (2014) have shown empirically an increasing (and U-shaped) relation between the number (and breadth) of the trademarks held by a private firm and its VC valuation, we show that the number of trademarks held by a firm at first VC investment has predictive power for its future operating performance, namely, its long-run sales, its long-run employment, and its propensity for successful exit, and is negatively related to the extent of VC investment staging in the firm. Our research is also related to the work of Fisch et al. (2022), who use European data and show that the breadth of trademarks held by a firm is positively related to its IPO valuation and post-IPO stock returns.

Practical Implications

The insights generated from our theoretical analysis and empirical findings have important implications for entrepreneurs, venture capitalists, angels, and other investors in entrepreneurial firms; intermediaries such as investment banks and institutional and retail investors in the IPO market; and policymakers. First, our results imply that it may be in the best interest of entrepreneurs to trademark as many of their firms' higher-quality products as possible while leaving lower-quality products without trademarks. Furthermore, in choosing products to trademark, they should not only consider the benefits from increased sales of trademarked products but also consider the benefits of attracting potentially larger amounts of funding from value-adding investors such as venture capitalists and IPO market investors, given the fact that the number of trademarks is likely to signal higher firm quality to these investors. Second, our empirical findings suggest that private firms with a larger number of trademarks can be expected to have better performance in terms of their long-run sales and employment. Third, our empirical findings suggest that private firms with a larger number of trademarks are more likely to have a successful exit (in terms of achieving an IPO or acquisition). Consistent with this, venture capitalists and angels are likely to award such firms higher valuations and make their total investment over a smaller number of rounds. Finally, our analysis suggests that, similar to reforms of the patenting process, it may also be beneficial for policymakers to reduce the costs of obtaining and maintaining trademarks (especially the costs associated with "trademark opposition") since such cost reduction may encourage entrepreneurs to trademark a larger number of their products, thereby enhancing the success probabilities of their firms.

Limitations and Avenues for Future Research

Both our theoretical model and empirical analysis are "static" in the sense that our analysis in this paper focuses on how VCs use the number of trademarks acquired by a firm at the time of the first VC investment to infer its intrinsic value, and how this number predicts its future operating performance captured by variables such as its long-run sales and employment and also predicts its propensity for successful exit. To align our empirical analysis precisely with the predictions of our theoretical model (and for comparability across firms), we choose as our main test variable the number of trademarks acquired by a firm in the few years immediately before the first VC investment (we choose 5 years, but our results are robust to choosing a smaller number of years). Our empirical analysis generated findings consistent with the predictions of our theoretical model.

As a result of our static focus, however, we have chosen to leave several interesting research questions on the dynamic evolution of the number of trademarks held by a firm to future researchers. We will mention two of these research questions here. First, how does the number of trademarks held by a firm evolve over time (e.g., do firms acquire more trademarks as the number of years passes after the year of founding)? Second, how does the number of trademarks held by a firm change in the years after the first VC investment in the firm, and in particular, what is the effect of VC investment on the number of trademarks held by a firm? These research questions, while interesting, are quite different from those we study in this paper. In particular, the second research question we mention above is almost the inverse of the question we study here, since, rather than analyzing (as we do in this paper) how the number of trademarks acquired by a firm prior to the first VC investment affects a VC's evaluation of the firm and its predictions about the firm's future operating performance, the above research question deals with how VC investment in a firm affects the firm's future acquisition of trademarks (and in particular, how the number of trademarks held by a firm evolves across VC financing rounds). We therefore believe that the examination of such research questions, while interesting, belongs to a future research paper.

Another limitation of our study is that our empirical results may be valid only for VC-backed private firms, given that our sample in this paper consists only of such firms. While our staging result on the relation between the number of trademarks and VC staging is relevant only for VC-backed private firms, it would be appropriate for future research to analyze the effect of trademarks on sales, employment, and the propensity for successful exit for non-VC backed private firms as well.

Acknowledgments

For helpful comments and suggestions, we thank Karthik Krishnan, Jie He, Karen Simonyan, Ann Sherman, Michael Ewens, David Mauer, Yongqiang Chu, Ahmet C. Kurt, Abu Jalal, Lin Guo, William Johnson, Laura Field, Michelle Lowry, Xiaohui Gao, Connie Mao, Gang Hu, Mark Grinblatt, Vesa Pursiainen, Erik Gilje, and Elizabeth Berger. We also thank seminar participants at Boston College, Lehigh University, Tsinghua PBC School of Finance, UNC Charlotte, Hong Kong Polytechnic University, Temple University, and Suffolk University, and conference participants at the Emerging Trends in Entrepreneurial Finance conference at Stevens Institute of Technology, the Philly Five Conference, the American Finance Association Meeting doctoral student session, the Midwest Finance Association Meetings, the China International Finance Conference (CICF), the Financial Management Association Meetings, the KWC Conference on Entrepreneurial Finance, the Boca Corporate Finance and Governance Conference, the 2021 Eastern Finance Association Annual Conference, the 2021 Northern Finance Association Annual Conference, the 2021 Indian Finance Conference, and the 2022 ASSA Annual Meeting. Special thanks to the editor, Armin Schwienbacher, and three anonymous referees for numerous comments which helped to greatly improve the paper.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Thomas Chemmanur acknowledges summer research support from Boston College and additional financial support from a Hillenbrand Distinguished Fellowship. Thomas Chemmanur and Qianqian Yu also acknowledge financial support from a Kauffman Foundation Knowledge Challenge Grant. Thomas Chemmanur and Harshit Rajaiya also acknowledge support from the Social Sciences and Humanities Research Council Insight Development Grant (Grant No. 430-2021-00342). Xuan Tian acknowledges financial support from the National Natural Science Foundation of China (Grant No. 72425002). Qianqian Yu acknowledges summer research support from the College of Business at Lehigh University. All remaining errors and omissions remain the responsibility of the authors.

ORCID iDs

Thomas J. Chemmanur https://orcid.org/0000-0003-3302-8977
Qianqian Yu https://orcid.org/0000-0002-0281-0002

Supplemental Material

Supplemental material for this article is available online.

Notes

1. We will discuss this literature in detail in the next section.
2. As we discuss in detail in Section B2 in Supplemental Appendix B, there are significant 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 the American Intellectual Property Law Association (AIPLA), Gaddis et al. (2015) mention that the median cost to a party in trademark opposition is $80,000.
3. Some papers in the literature have argued that there is a correlation between trademark activity and various measures of innovation (Faurel et al., 2016; Mendonça et al., 2004). However, we find that the correlation between trademarks and patents for entrepreneurial firms is small, namely around 0.2. Furthermore, we control for patents and citations in all our analyses to demonstrate that our results on the relation between the number of trademarks and various outcome variables with respect to startup firms are independent of the effects of patents on these variables.
4. Private firm valuation is notoriously hard to do, even for VCs, and in addition, the results of Block et al. (2014) are heavily dependent on the coverage of private firm valuation in VentureXpert, which has missing information on the valuation of private firms for a significant fraction of firms. By contrast, the operating performance variables we use: sales, employment, and successful exit are fundamentally different measures and are directly observable. They are also much less prone to error.
5. Our paper is also related to the broader literature on the effect of intellectual property on various firm characteristics: see Besen and Raskind (1991) for an excellent review.
6. Heath and Mace (2020) studied the effects of trademark protection on firms' profits and strategy using the 1996 Federal Trademark Dilution Act, which granted additional legal protection to selected trademarks. They find that stronger trademark protection has a negative effect on innovation and product quality.
7. In a subsequent paper, Yang and Yuan (2022) study the relationship between trademarks and IPO underpricing, which is not the focus of this paper.
8. We assume that the entrepreneur (firm insider) sells a fraction α of his equity holdings to outside investors due to his portfolio diversification motive or the firm's investment requirement or both. For simplicity, we assume that the firm is selling equity alone (rather than a combination of equity and some other security such as debt) to abstract away from complications related to security design, which is not the focus of this paper.
9. One should note that type L products are not necessarily bad products. We only assume that the quality of type L products is lower relative to type H products in the sense described above about the firm's expected cash flows from these products.
10. We assume that outsiders' prior beliefs about product quality are independently and identically distributed within the product portfolio of each firm.
11. Note that a firm with a single product (i.e., $N = 1$) is a special case of our model. All of our results continue to hold in this special case.
12. This assumption is only for analytical simplicity. Our results will go through as long as k_H is significantly greater than k_L.
13. This is a natural assumption to make here. Recall that the product market benefits of trademarks operate through channels such as consumer loyalty, which will yield greater cash flows to the firm if the product is truly of higher quality since a customer who buys a product of higher quality is more likely to make repeat purchases of the product compared to the case where the product is of lower quality.

14. Asymmetric information about product quality matters more for start-up firms, which is the focus of this paper. Clearly, for established firms with a longer track record in the product market, the extent of asymmetric information about product quality may be smaller.
15. While we do not wish to claim that this equilibrium is unique, it can be shown that this equilibrium satisfies the Intuitive Criterion (Cho & Kreps, 1987), thus showing the stability of this equilibrium. By contrast, for the parameter values specified in Proposition 1, other equilibria that may exist (especially pooling equilibria) do not, in general, survive the Intuitive Criterion and are therefore eliminated as stable equilibria in our setting.
16. For tractability, we have adopted a model with only two quality levels, high (H) and low (L) corresponding to $q_i = 1$ and $q_i = 0$, respectively, and showed that an informative separating equilibrium exists under the parametric restriction on C specified in Proposition 1. It can be shown that in a more complex model with a continuum of product quality settings (perhaps approximating the real world more closely), with product quality q_i uniformly distributed over [0, 1], where $q_i = 0$ corresponds to type L and $q_i = 1$ corresponds to type H, and the cash flow benefit from trademarking increasing in product quality (and with all other assumptions similar to that in the model presented here), there always exists an equilibrium where firms trademark all products with product quality above a critical value, while not trademarking products with quality below this critical value. In such an equilibrium, the number of trademarks held by a private firm will reveal some of the entrepreneur's private information about the firm value to outside investors (such as VCs). However, this equilibrium, while informative, will not be fully revealing: that is, observing the number of trademarks will reveal to outside investors some (but not all) information held by the entrepreneur about the quality of his firm's products.
17. As Mendonça et al. (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.
18. 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 can 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 similarities 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).
19. Thus, it should be noted that the theoretical model of trademarks we present here is a "productive signaling" model, where trademarks increase the cash flows of a firm's high-quality products, and therefore the cash flows for the firm as a whole. In this sense, our model differs from the classical model of signaling by Spence (1973), where education is a dissipative signal (i.e., where a student's education plays only a signaling role to employers and does not enhance worker's labor productivity).
20. The model of VC investment staging that we develop here is somewhat in the spirit of Jensen (1986) where he outlines an informal "free cash flow" theory for public firms. The idea here is that CEOs like to retain a public firm's free cash flow (i.e., cash flow available to the firm in excess of the investment requirements of the positive NPV projects available to it) and may waste some of this cash flow by investing in some negative NPV projects.
21. In practice, the VC's total investment period for a portfolio company, that is, the time period from the first VC financing round until the VCs harvest their returns on investment from the portfolio company (private firm) through an exit, is between 3 and 5 years on average. None of our results will be qualitatively affected by this normalizing assumption, made for tractability.
22. In practice, the amount disbursed can vary across rounds and, further, the time interval between rounds can also be different across successive rounds. Allowing these real-world aspects into the model will add complexity to our model without providing commensurate insights.

23. Notice that the wastage of VC investment funds by a private firm depends not only on the amount disbursed per round I/M but also on the length of time the amount stays invested in the firm. For example, a fraction κ of the entire amount (I/M) invested in the first round is wasted by the firm since it stays invested in the firm for all rounds, but the amount I/M disbursed in the second round stays invested only for ($M-1$) rounds so that it stays invested in the firm only for a fraction $(M - j + 1)/M$ of the total investment period. In general, an amount I/M disbursed in round j will stay invested in the firm only for a fraction $(M - j + 1)/M$ of the total investment period (normalized to 1 here).
24. The assumption that κ is decreasing in the aggregate NPV of the projects available to the firm captures the notion that private firms are less likely to waste VC investments when they have a larger number of higher NPV projects available to them. This assumption is also in the spirit of Jensen's (1986) free cash flow idea, where "free cash flow" is defined as cash flows in excess of the aggregate investment requirements in all the positive NPV projects available to a firm. Given that the equilibrium scale of higher NPV projects (defined as the scale where the NPV of the last dollar of investment falls to zero) is larger, the free cash flows available to firms with a larger number of high-quality products (larger NPV projects) will be smaller so that the fraction of the total available investment amount wasted by the entrepreneur will be smaller as well.
25. This result illustrates the benefit of staging in our model, which is to minimize the aggregate free cash flow (total amount invested by VCs minus the investment requirement of positive NPV projects available to the firm) available for wastage by the private firm over the entire VC investment period. Since the private firm will waste a fraction of the free cash flow available to the firm at any given point in time, the VC's incentive (if contracting costs were zero) would be to exactly match the amount disbursed per round to the investment requirements of the private firm at that point so that the free cash flow available for wastage is minimized.
26. In this more complex setting, outsiders will only be able to infer the expected number (i.e., the average across firms) of high-quality products developed by the firm from observing the number of trademarks registered by it. In other words, while, in this more complex setting, the number of trademarks held by firms will continue to convey information about the firm's intrinsic value to outsiders, this information will be noisy.
27. We focus on VC-backed private firms since the detailed data on non-VC-backed private firms required for our exit analysis are not easily available. Furthermore, it has been documented that VC-backed firms play a more important role in the U.S. economy, representing an important driver for economic growth and employment.
28. See Neumark et al. (2010) for a more detailed description of the NETS data set.
29. We started in 1985 to measure trademarks from 5 years prior to the first round of VC investment.
30. We choose 5 years to ensure that the information is not stale, which may be the case if we choose 10 years. In untabulated tests, we find that our results are robust to using a smaller number of years such as 2 years.
31. Note that all the variables are winsorized at the 1st and 99th percentiles except for the number of trademarks and trademark applications.
32. If a VC-backed firm did not receive any VC investment in the 5 years after the last VC investment, we treat it as a case of "no exit" or consider it equivalent to a write-off.
33. Gaule (2018) and Melero et al. (2020) use average patent examiner leniency as an instrument for patent grants in their research.
34. Please refer to Section B2 in Supplemental Appendix B for details on the trademark application process; also refer to Graham et al. (2013) for a detailed study on the life cycle of trademark applications.
35. By quality of application, we refer to the information provided by the applicant in the application, which may help to distinguish its mark from existing marks owned by other entities.
36. We show in Table B1 of Supplemental Appendix B that our examiner leniency measure is uncorrelated with firm characteristics.

37. 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 across-examiner variation.
38. Our IV results also hold even if we consider all the trademark applications filed over a different time horizon such as a 3-year or a 1-year period.
39. 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.
40. In untabulated tests, we find that our baseline analysis results hold even if we conduct these analyses on the sample of firms with at least one trademark application in the 2-year period prior to the first round of VC investment. In other words, our baseline analysis results are robust to only considering firms that comprise our IV analysis sample.
41. In Table B3 in Supplemental Appendix B, we show that our results on sales are robust to measuring trademarks using an indicator variable. Thus, even on the extensive margin, trademarks are associated with greater long-run sales.
42. We use the same set of control variables as in our earlier analysis on VC staging. However, we suppress the coefficients of control variables in both panels to conserve space.
43. In Table B4 in Supplemental Appendix B, we show that our results on employment are robust to measuring trademarks using an indicator variable. Thus, even on the extensive margin, trademarks are associated with greater long-run employment.
44. We suppress the coefficients of control variables in both panels to conserve space.
45. In Table B5 in Supplemental Appendix B, we show that our results on successful exit are robust to measuring trademarks using an indicator variable. Thus, even on the extensive margin, trademarks are associated with a greater likelihood of successful exits.
46. In an untabulated analysis suggested by an anonymous referee, we find that our results are also robust to considering two alternative measures of successful acquisitions. First, following Ewens and Marx (2018), we consider an acquisition successful only if the valuation of a startup is at least 1.25 times the total amount of VC funding in the startup. Second, our results are also robust to considering only those acquisitions as successful where the valuation is above $25 million US dollars (following Bernstein et al., 2016). We obtain the data for this acquisition valuation analysis from the SDC M&A database. In both the above specifications, we consider all acquisitions where there is no data on the valuation as failures following Ewens and Marx (2018). We do not use these criteria for successful acquisitions in our main specification since this valuation information is available for only around 20% of acquisitions on the SDC M&A database.
47. In an untabulated test, we find that our results are also robust to using a multinomial logit regression.
48. Note that our baseline and IV analyses are robust to using a probit model.

References

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion.* Princeton University Press.

Athreye, S., & Fassio, C. (2021). Why do innovators not apply for trademarks? The role of information asymmetries and collaborative innovation. In Carolina Castaldi, Jörn Block & Meindert J. Flikkema (Eds.), *Trademarks and their role in innovation, entrepreneurship and industrial organization* (pp. 237–257). Routledge.

Bernstein, S., Giroud, X., & Townsend, R. R. (2016). The impact of venture capital monitoring. *The Journal of Finance*, *71*, 1591–1622.

Besen, S. M., & Raskind, L. J. (1991). An introduction to the law and economics of intellectual property. *Journal of Economic Perspectives*, *5*, 3–27.

Block, J. H., Fisch, C. O., Hahn, A., & Sandner, P. G. (2015). Why do SMEs file trademarks? Insights from firms in innovative industries. *Research Policy*, *44*, 1915–1930.

Block, J. H., De Vries, G. D., Schumann, J. H., & Sandner, P. (2014). Trademarks and venture capital valuation. *Journal of Business Venturing*, *29*, 525–542.

Castaldi, C. (2018). To trademark or not to trademark: The case of the creative and cultural industries. *Research Policy*, *47*, 606–616.

Chemmanur, T. J., & Fulghieri, P. (1999). A theory of the going-public decision. *The Review of Financial Studies*, *12*, 249–279.

Chemmanur, T. J., He, S., & Nandy, D. K. (2009). The going-public decision and the product market. *The Review of Financial Studies*, *23*, 1855–1908.

Chemmanur, T., & Yan, A. (2009). Product market advertising and new equity issues. *Journal of Financial Economics*, *92*(1), 40–65.

Cho, I. K., & Kreps, D. M. (1987). Signaling games and stable equilibria. *The Quarterly Journal of Economics*, *102*(2), 179–221.

Economides, N. S. (1988). The economics of trademarks. *Trademark Reporter*, *78*, 523.

Ewens, M., & Marx, M. (2018). Founder replacement and startup performance. *The Review of Financial Studies*, *31*, 1532–1565.

Faurel, L., Li, Q., Shanthikumar, D. M., & Teoh, S. H. (2016). *CEO incentives and new product development: Insights from trademarks* (Working Paper). University of California, Irvine.

Ferreira, D., Manso, G., & Silva, A. C. (2014). Incentives to innovate and the decision to go public or private. *The Review of Financial Studies*, *27*, 256–300.

Fisch, C., Meoli, M., Vismara, S., & Block, J. H. (2022). The effect of trademark breadth on IPO valuation and post-IPO performance: An empirical investigation of 1510 European IPOs. *Journal of Business Venturing*, *37*, 106237.

Gaddis, B. A., Garboczi, P., Stewartson, C., & Reid, B. E. (2015). *Discouraging frivolous claims in trademark opposition proceedings: A policy proposal to the United States patent and trademark office* (Working Paper). University of Colorado Law School.

Gaule, P. (2018). Patents and the success of venture-capital backed startups: Using examiner assignment to estimate causal effects. *The Journal of Industrial Economics*, *66*, 350–376.

Graham, S. J., Hancock, G., Marco, A. C., & Myers, A. F. (2013). The USPTO trademark case files dataset: Descriptions, lessons, and insights. *Journal of Economics and Management Strategy*, *22*, 669–705.

Hall, B., Jaffe, A., & Trajtenberg, M. (2001). *The NBER patent citation data file: Lessons, insights and methodological tools* (NBER Working Paper 8498). NBER.

Heath, D., & Mace, C. (2020). The strategic effects of trademark protection. *The Review of Financial Studies*, *33*, 1848–1877.

Hsu, P.-H., Li, K., Liu, Y., & Wu, H. (2017). *Product market dynamics and mergers and acquisitions: Insights from the USPTO trademark data* (Working Paper). University of British Columbia.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, *76*, 323–329.

Landes, W. M., & Posner, R. A. (1987). Trademark law: An economic perspective. *The Journal of Law and Economics*, *30*, 265–309.

Long, C. (2002). *Patent signals* (pp.625–679). The University of Chicago Law Review.

Melero, E., Palomeras, N., & Wehrheim, D. (2020). The effect of patent protection on inventor mobility. *Management Science*, *66*, 5485–5504.

Mendonça, S., Pereira, T. S., & Godinho, M. M. (2004). Trademarks as an indicator of innovation and industrial change. *Research Policy*, *33*, 1385–1404.

Nahata, R. (2008). Venture capital reputation and investment performance. *Journal of Financial Economics*, *90*, 127–151.

Neumark, D., Wall, B., & Zhang, J. (2010). Do small businesses create more jobs? New evidence for the united states from the National Establishment Time Series. *The Review of Economics and Statistics*, *93*, 16–29.

Sandner, P. G., & Block, J. (2011). The market value of R&D, patents, and trademarks. *Research Policy*, *40*, 969–985.
Schwienbacher, A. (2008). Innovation and venture capital exits. *The Economic Journal*, *118*, 1888–1916.
Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and R&D activity. *Journal of Financial Economics*, *111*, 381–405.
Sherman, A. E., & Titman, S. (2002). Building the IPO order book: Underpricing and participation limits with costly information. *Journal of Financial Economics*, *65*, 3–29.
Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, *87*(3), 355–374. https://doi.org/10.2307/1882010
Spiegel, M., & Tookes, H. (2020). Why does an IPO affect rival firms? *The Review of Financial Studies*, *33*, 3205–3249.
Stock, J. H., & Yogo, M. (2002). *Testing for weak instruments in linear IV regression* (Working Paper 284). National Bureau of Economic Research.
Uzuegbunam, I., Ofem, B., & Nambisan, S. (2019). Do corporate investors affect entrepreneurs' IP portfolio? Entrepreneurial finance and intellectual property in new firms. *Entrepreneurship Theory and Practice*, *43*, 673–696.
Yang, B., & Yuan, T. (2022). Trademark and IPO underpricing. *Financial Management*, *51*, 271–296.
Zhou, H., Sandner, P. G., Martinelli, S. L., & Block, J. H. (2016). Patents, trademarks, and their complementarity in venture capital funding. *Technovation*, *47*, 14–22.

Author Biographies

Onur Bayar is Professor of Finance at the Alvarez College of Business, University of Texas at San Antonio. He earned his Ph.D. degree in Finance from Boston College and his M.S. degree in Financial Economics from Carnegie Mellon University. Onur's research interests are in theoretical and empirical corporate finance, entrepreneurial finance, and topics in applied game theory and contract theory, with an emphasis on initial public offerings, mergers & acquisitions, venture capital, securities issuance, capital structure, payout policy, corporate restructuring, and corporate innovation. Onur has published several research articles in leading finance and innovation journals, and he has served as an ad hoc referee for various academic journals in finance and economics.

Thomas J. Chemmanur is currently a Professor of Finance at the Carroll School of Management, Boston College. He is an award-winning researcher in the areas of theoretical and empirical corporate finance, entrepreneurial finance, and financial intermediation with special research interests in the areas of venture capital, initial public offerings, corporate innovation, corporate restructuring, and corporate governance. He has over 60 academic papers published in the leading finance and entrepreneurship journals. He has served as an Associate Editor of several top finance journals such as the *Review of Financial Studies* and *Financial Management*, and is currently serving as an Associate Editor of the *Journal of Banking and Finance*, *Review of Corporate Finance*, *Review of Quantitative Finance and Accounting, International Review of Finance* and the *Journal of Economics and Business*. He has edited special issues of several leading journals including the *Journal of Financial Intermediation*, the *Journal of Corporate Finance*, and the *Journal of Economics and Business* in the areas of entrepreneurial finance and corporate finance. He has organized and serves on the program committees of several top academic conferences.

Harshit Rajaiya is an Assistant Professor of Finance at the Telfer School of Management at the University of Ottawa. His research interests are in entrepreneurial finance and corporate finance. His research papers have covered several topics in corporate innovation, venture capital, fintech, student loans, and financial policies. Harshit has published in leading finance and entrepreneurship journals.

Xuan Tian is the JD Capital Chair Professor of Finance at PBC School of Finance, Tsinghua University. He is also the "Cheung Kong Scholar" Distinguished Professor and a member of academic council of Tsinghua University. Xuan is an award winning researcher in the areas of corporate finance and financial intermediation with special research interests on venture capital, corporate innovation, and capital markets. He has more than 50 academic papers published in leading academic journals. Xuan was a co-editor of Journal of Corporate Finance, and is serving as Associate Editor of *Management Science*, *Journal of Banking and Finance*, and *China Economic Review*. He serves as the program chair and committee member of many top academic conferences and an ad hoc referee for over 30 academic journals.

Qianqian Yu is an Assistant Professor of Finance at the College of Business at Lehigh University. Her research interests are in entrepreneurial finance and corporate finance, with a focus on venture capital, corporate innovation, and initial public offerings. Qianqian has published papers in leading finance, entrepreneurship, and management journals.