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THREE ESSAYS IN CORPORATE AND ENTREPRENEURIAL FINANCE

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Abstract

My dissertation consists of three chapters. In the first chapter, I analyze the impact of firms' innovation success on their corporate financial policies. I hypothesize that innovation success reduces the information asymmetry facing firms and, through the information channel, affects their capital structure and dividend policies. I measure innovation success using the quantity and quality of patents. I show that firms with higher innovation success face lower information asymmetry, measured using analyst coverage, dispersion, and forecast error. Further, I show that firms with higher innovation success have lower leverage ratios; have a greater propensity to issue equity rather than debt; and have lower dividend payout ratios. I establish causality using instrumental variable analyses with patent examiner leniency as an instrument for patent grants.

In the second chapter, co-authored with Thomas Chemmanur, Xuan Tian, and Qianqian Yu, we analyze the impact of trademarks in entrepreneurial firms' success. We hypothesize that trademarks play two economically important roles for entrepreneurial firms: a "protective" role, leading to

better product market performance; and an "informational" role, signaling higher firm quality to investors. We develop testable hypotheses based on the above two roles of trademarks, relating the trademarks held by private firms to the characteristics of venture capital (VC) investment in them, their probability of successful exit, their valuations at their initial public offering (IPO) and in the immediate secondary market; institutional investor IPO participation; post-IPO information asymmetry; and post-IPO operating performance. We test these hypotheses using a large and unique dataset of trademarks held by VC-backed private firms. We establish causality using an instrumental variable (IV) analysis using trademark examiner leniency as the instrument. For private firms, we find that the number of trademarks held by the firm is positively related to the total amount invested by VCs and negatively related to the extent of staging by VCs. We show that the number of trademarks held by a firm increases its probability of successful exit (IPOs or acquisitions). Further, for the subsample of VC-backed firms going public, we show that the number of trademarks held by the firm leads to higher IPO and immediate secondary market firm valuations; greater IPO participation by institutional investors; a lower extent of information asymmetry in the equity market post-IPO; and better post-IPO operating performance.

In the third chapter, co-authored with Thomas Chemmanur and Jinfei Sheng, we develop testable hypotheses and empirically analyze the effects of outside investors having access to soft information such as online employee ratings from the Glassdoor website on firms' financing and investment policies. We find that higher online employee ratings are associated with larger equity issue announcement effects; a greater propensity to have positive announcement effects and to issue equity rather than debt to raise external financing; higher investment expenditures; greater equity issue participation by institutional investors; and better long-run post-issue operating performance. We establish causality using a difference-in-differences methodology relying on the staggered adoption of anti-SLAPP laws across U.S. states.

Dedication

To my parents, Vijay Rajaiya and Kumud Rajaiya

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Finally, on a personal note, I am grateful to my parents for their moral support and encouragement throughout these years and especially during tough times. I learnt a lot from my father about discipline and work ethic. I am grateful to my mother for teaching me the importance of having a positive attitude in life.

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Chapter 1

Innovation Success and Corporate Financial Policies

1.1 Introduction

Even after more than half a century since Modigliani and Miller's seminal papers (Modigliani and Miller (1958) and Miller and Modigliani (1961)) on the irrelevance of financial policies of firms, there is still considerable debate on the factors that determine the financial policies of corporations (namely, capital structure and dividend policies). Information asymmetry is an important channel that affects these two important financial policies of firms: the capital structure and the dividend payout ratio. In this paper, I hypothesize that innovation success is an important factor that affects the financial policies of firms by reducing the extent of information asymmetry that they face in the equity market.

U.S. firms invest a substantial amount in providing input to innovation. The National Science Foundation (NSF) estimates that U.S. businesses spent around 355 billion dollars on research and development (R&D) activities in 2015.[1] Further, U.S. firms also dominate the list of the most innovative firms in the world.[2] In a setting with information asymmetry between firm insiders and outside investors, patents certify the value of firms to outside investors.[3] A patent grant is a validation by the United States Patent and Trademark Office (USPTO), an independent government agency, certifying a firm's research by validating that it meets their criteria for patenting. Additionally, patenting is a costly process with direct and indirect costs associated with them including R&D expenditures, patent application costs, patent maintenance costs, and protection costs, e.g., litigation costs. This means that a patent granted to a firm is not easy to mimic by a firm which has only lower quality research. Hence, in a setting with information asymmetry between firm insiders and outside investors, innovation success (quantity and quality of patents) may act as a signal of

[1] See, e.g., the following link on NSF website: https://www.nsf.gov/statistics/2018/nsf18306/.

[2] See, e.g., an article in USA Today, titled, "The world's most innovative companies:" https://www.usatoday.com/story/money/business/2018/01/12/worlds-50-most-innovative-companies/1023095001/.

[3] For example, think of a biotech firm which is conducting research on developing a new drug for Alzheimer's disease and has filed for a patent for this drug molecule before conducting human clinical trials. The firm insiders may not able to credibly convey the quality and progress of its research by making a public announcement. However, patents act as a credible mechanism through which firms convey the value and progress of their research to outsiders.

firm quality to investors.

A reduction in the information asymmetry, in turn, may lead the firm to issue more equity rather than debt to fund its projects. As Myers and Majluf (1984) argue, equity is the most "information sensitive" security that a firm can issue, so that, in the presence of information asymmetry, firms prefer to issue debt rather than equity to raise external finance. However, debt has its own costs arising from various market imperfections such as the cost of financial distress associated with the extent of debt in the capital structure (see, e.g., Bradley, Jarrell, and Kim (1984) and Shyam-Sunder and Myers (1999)). *Ceteris paribus*, a reduction in information asymmetry will lower the cost of issuing equity leading to lower leverage ratios. Further, firms with higher innovation success will need to rely less on dividend payouts to signal their intrinsic value to outsiders, again through the reduced information asymmetry channel.[4] Thus, innovation success may shape these two financial policies of firms by reducing the extent of information asymmetry facing firms in the equity market.

The impact of innovation success on firms' capital structures is an interesting empirical puzzle. On the one hand, innovation success may reduce the information asymmetry faced by firms in the equity market. This, in turn, will lower the cost of issuing equity, but will have very little effect on costs associated with debt. This is because equity as a security is much more information sensitive than debt (Myers and Majluf (1984)). On the other hand, innovation success may reduce the uncertainty faced by investors about a firm's prospects (i.e., firm riskiness). In a Modigliani and Miller (1958) world (perfect capital market), a reduction only in a firm's riskiness will have no effect on its capital structure. Therefore, the impact of innovation success on firms' capital structures is an empirical question, which I address in this paper.

I analyze the relationship between firms' innovation success (as captured by the quantity and quality of their innovation output) and their financial policies, namely, capital structure and dividend policies. I use patent-based measures to capture the quantity and quality of innovation output (innovation success) of a firm. In particular, I use the stock of patents held by firms and their citations per patent as proxies for innovation output. The patents granted to a firm captures the quantity of innovation output, whereas the citations per patent capture the economic or scientific value (quality) of the patent. These measures are standard in the literature. Therefore, as dis-

[4]See, e.g., Miller and Rock (1985) or John and Williams (1985), who argue that dividends are used as signals to convey information about the intrinsic value of firms to outsiders.

cussed earlier, patents and citations may certify the intrinsic values of firms to the equity market and reduce the extent of information asymmetry facing firms in the equity market.

On the basis of the above arguments, I develop testable hypotheses regarding the impact of firms' innovation success on the information asymmetry they face in the equity market, and through the information asymmetry channel, on their capital structure and dividend policies. I now summarize these testable hypotheses. First, firms with a larger number of patents and a higher quality of patents (as captured by citations per patent) will face a smaller extent of information asymmetry in the equity market. Second, such firms will have lower leverage ratios, *ceteris paribus*, since they face a smaller extent of information asymmetry in the equity market. Third, using similar arguments, firms with higher innovation success will have a greater propensity to issue equity rather than debt to raise external financing. Finally, firms with higher innovation success will have lower dividend payout ratios, since they need to signal only to a smaller extent because of the smaller extent of information asymmetry that they face in the equity market.

I analyze the above hypotheses on the relationship between innovation success and the financial policies of firms using panel data on U.S. public firms from the Compustat database. My sample period begins in 1981 and ends in 2016 covering all public non-financial and non-utility firms. I obtain patents and citations data from the following sources: the NBER Patent Project, the Harvard Dataverse, the United States Patent and Trademark (USPTO) website, the USPTO Patent Application Information Retrieval (PAIR) dataset, and the USPTO Patent Assignment dataset. Following the innovation literature, I construct standard measures of innovation success (i.e., innovation output). I obtain analyst coverage information from the Institutional Brokers' Estimation System (IBES) database to construct the following measures of information asymmetry used in the corporate finance literature: the number of analysts following a firm, the standard deviation of analyst forecasts, and the mean analyst forecast error.

As a starting point, I run ordinary least squares (OLS) regressions as baseline analyses to test my hypotheses. However, my baseline analyses may suffer from some endogeneity problems. For example, higher quality firms may have greater innovation success while at the same time, have cheaper access to the equity market. To address these potential endogeneity concerns, I run instrumental variable (IV) analyses, instrumenting for patents granted to firms using a measure of patent examiner leniency. Conditional on technology and year, patent applications are randomly assigned to patent examiners, who are affiliated to particular "art-units," and who accept or reject these applications. Prior literature suggests that the patent review process leaves significant discretion to patent examiners.[5] Patent examiners differ in their tendency to accept or reject patent applications (leniency). Thus, patent applications are likely to be affected by the exogenous variation in the leniency of patent examiners. Therefore, in my IV analysis, I restrict my sample to the set of firms filing patent applications. For any firm, I instrument the number of patent applications which are eventually granted using the average art-unit-adjusted examiner leniency calculated across all patent applications (accepted or rejected) filed by a firm in a rolling three-year period.[6] For the above analysis, I collect patent application data from the PAIR database. For each application, PAIR provides information on the filing date, patent class and subclass, current application status, examiner name, examiner identification, and the corresponding art-unit.

My empirical results may be summarized as follows. First, using my baseline analysis, I establish that firms with higher innovation success face a lower extent of information asymmetry in the equity market. These results are both statistically and economically significant. For instance, a one standard deviation increase in the log measure of the stock of patents held by a firm leads to a 13.2 percentage point increase in the log number of analysts following the firm, which implies a 16.1% increase in the average value of analyst coverage. A one standard deviation increase in the log measure of the stock of patents held by a firm leads to a 22.1% decrease in the average value of analyst forecast dispersion and a 24.7% decrease in the average value of analyst forecast error, implying a smaller extent of information asymmetry faced by firms with higher innovation success. My IV analysis establishes that the above results are causal.

Second, I establish, using my baseline analyses, that innovation success affects the capital structures of firms. I demonstrate that firms with higher innovation success have lower leverage ratios. A one standard deviation increase in the log measure of the stock of patents held by a firm leads to a 4.5% decrease in the average value of book leverage. Additionally, such firms have a greater propensity to issue equity over debt to raise external finance. A one standard deviation increase in the log measure of a firm's stock of patents leads to a 9.9% increase in the average probability of issuing equity rather than debt. My IV analysis establishes that the above results

[5] See, e.g., Lemley and Sampat (2012) and Sampat and Williams (2019).

[6] The above instrument is similar to the instruments that have been used in the existing innovation literature. See, e.g., Sampat and Williams (2019), Farre-Mensa, Hegde, and Ljungqvist (2019), and Gaule (2018).

are causal.

Third, I establish that innovation success affects the capital structure through the information asymmetry channel. I use information asymmetry variables as controls in my baseline regressions on capital structure, using innovation success measures as the main independent variables. I show that the coefficients of innovation success measures are smaller in magnitude when I use information asymmetry variables as controls, compared to the case when I do not use information asymmetry variables as controls. This result suggests that innovation success affects the capital structure through the information asymmetry channel. Further, I show that the coefficients of analyst coverage are negative and significant. Additionally, I show that the coefficients of analyst dispersion and forecast error are positive and significant. This implies that firms with lower analyst dispersion and lower analyst forecast error, i.e., firms with lower information asymmetry, have lower leverage ratios.

Fourth, I provide evidence that innovation success affects firms' dividend policies. Using my baseline analysis, I show that firms with higher innovation success have lower dividend payout ratios. A one standard deviation increase in the log measure of the stock of a firm's patents leads to a 5.6% decrease in the mean dividend payout ratio. My IV analysis establishes that the above results are causal.

I conduct robustness tests by using two additional measures of innovation success. First, I use a proxy for the economic value of patents following Kogan, Papanikolaou, Seru, and Stoffman (2017), KPSS (2017) from now on, who capture the dollar value of patents based on the change in market capitalization of a firm in the stock market around the announcement of a patent grant to the firm. In particular, I use the log measure of the dollar value of all patents issued to a firm in a year normalized by its book value of assets. Second, following KPSS (2017), I use the natural logarithm of one plus cohort-adjusted (class-adjusted) forward citations to all patents granted to a firm in a year scaled by the book value of assets of the firm. My results are robust to using these measures. I show that firms that have patents with higher economic value (dollar value of patents) and higher scientific value (captured by the normalized weighted citations measure) face a smaller extent of information asymmetry in the equity market, have lower leverage ratios, and have a greater propensity to issue equity rather than debt to raise external finance.

Finally, I provide additional evidence showing that my results are driven by the information asymmetry channel. I conduct cross-sectional analyses across firms facing lower versus higher information asymmetry and separately, across age groups of firms. I show that the impact of innovation success on financial policies is stronger for firms facing higher information asymmetry, which is expected. Using interaction tests, I show that the same level of innovation success leads to lower leverage ratios and lower dividend payout ratios for firms facing higher information asymmetry compared to firms facing lower information asymmetry. Further, using separate interaction tests, I show that the same level of innovation success reduces the information asymmetry for younger firms in the equity market to a greater extent than it does for older firms. Given that younger firms face a greater extent of information asymmetry compared to older firms, these results also support the information asymmetry channel. Using interaction tests, I also show that the same level of innovation success leads to lower leverage ratios and lower dividend payout ratios for younger firms compared to older firms. Finally, I discuss and rule out other channels, such as agency and bankruptcy cost-based explanations, which may also explain my results.

The rest of the paper is organized as follows. Section 2 describes the related literature and the contribution with respect to that literature. Section 3 outlines the underlying theory and develops hypotheses for my empirical tests. Section 4 describes the institutional details of the patent application process. Section 5 discusses my data and sample selection procedure. Section 6 provides a discussion on my identification strategy (IV analyses). Section 7, 8, and 9 discuss the impact of innovation success on information asymmetry, capital structure, and dividend policies, respectively. Section 10 discusses robustness and cross-sectional analyses. Section 11 discusses alternative channels through which innovation success may also affect the financial policies of firms and provides additional empirical evidence to rule out these channels. Section 12 concludes the paper.

1.2 Relation to the Existing Literature and Contribution

I contribute to several strands in the literature. The first strand is the literature on corporate innovation. The bulk of the innovation literature focuses on how various firm characteristics, e.g., managerial compensation (Ederer and Manso (2013)); conglomerate structure (e.g., Seru (2014)); anti-takeover provision (Chemmanur and Tian (2018); venture capitals' tolerance for failure (Tian and Wang (2011)); corporate venture capitalists rather than independent venture capitalists (Chemmanur, Loutskina, and Tian (2014)); top management quality (Chemmanur, Kong, Krishnan, and Yu (2019)) and shareholder litigation (Lin, Liu, and Manso (2016)) affect innovation in established firms. Another strand in this literature focuses on the valuation of innovation by the stock market: see, e.g., Cohen, Diether, and Malloy (2013); Hirshleifer, Hsu, and Li (2013); and Kogan, Papanikolaou, Seru, and Stoffman (2017).[7] Most of these papers study factors affecting corporate innovation. In contrast, I analyze, for the first time in the literature, the impact of innovation success on the financial policies of firms.

Second, I contribute to the literature on the financial policies of firms, particularly the large literature on capital structure and dividend policies. For example, using a cross country study, Rajan and Zingales (1995) demonstrate that firm size, profitability, asset tangibility, and Tobins'Q significantly affect the capital structures of firms. Titman (1984) argue that firms' liquidations impose costs on their customers, workers, or suppliers, leading to negative relationship between leverage ratio and liquidation costs. Titman and Wessels (1988) provide empirical evidence of the negative relationship between firms' liquidation costs and leverage ratios. There are also other firm characteristics that affect its capital structure, see, e.g., Chemmanur, Paeglis, and Simonayan (2009) provide evidence that higher top management quality leads to lower leverage ratios. Kisgen (2006) shows that credit rating affects the capital structures of firms. Using earnings release as proxy for information events, Korajczyk, Lucas, and McDonald (1991) show that firms issue equity after credible information events.[8] The announcement effect of dividend changes have been documented extensively in the literature, see, e.g., Asquith and Mullins (1983). Several papers test and find support for signaling models of dividends under asymmetric information: see, e.g., Bernheim and Wantz (1995) and Nissim and Ziv (2003).[9] In contrast, I show that innovation success reduces the information asymmetry faced by firms, leading to lower leverage ratios and lower dividend payout ratios.

Third, I also contribute indirectly to the literature that studies the impact of access to external financing on corporate innovation. Brown, Fazzari, and Petersen (2009) demonstrate that finance

[7]See, e.g., He and Tian (2018) for an excellent survey on innovation literature.

[8]See, e.g, Harris and Raviv (1991) for an excellent survey on capital structure theories and Graham and Leary (2011) for an excellent survey of empirical capital structure research.

[9]See, e.g., Allen and Michaely (2003) for an excellent survey of literature on payout policies of firms.

supply shifts explain the R&D boom in the 1990s. Using a cross-country study, Hsu, Tian, and Xu (2014) provide evidence that industries which are reliant on external finance and are more technology intensive show a higher innovation level in countries with better developed equity markets. In contrast, I analyze the impact of innovation success on the financial policies of firms.

A recent paper related to mine is Mann (2018), who exploits federal court rulings that increased creditor rights over patents in Delaware to show that Delaware incorporated firms may use patents as collateral to raise debt in the two years immediately following the law change. In contrast to the above paper, I analyze the entire universe of patents granted to all the U.S. public firms and document that patents help reduce the information asymmetry facing these public firms in the equity market, thereby leading to lower leverage ratios, a greater propensity to issue equity, and lower dividend payout ratios. My results on capital structure are opposite to that of Mann (2018). However, my results are universal, i.e., applies to a general firm in U.S., since, in contrast to Mann (2018), I include all the patents assigned to U.S. public firms, and not just patents used as collateral. Further, my results apply to all firms in U.S. and not only to Delaware incorporated firms as in Mann (2018).[10]

In summary, the main contribution of this paper is that it is the first paper in the literature to analyze the relationship between innovation success and the financial policies of firms. I document that firms with a higher quantity (measured by the number of patents) and higher quality (measured by citations per patent) of innovation output have lower leverage ratios. Further, I provide evidence that such firms have lower dividend payout ratios. I establish that the underlying channel through which a higher innovation success affects the financial policies of firms is by reducing the extent of information asymmetry facing firms in the equity market. Lastly, I show that the above results are causal using IV analysis, where I use the leniency of patent examiners as the instrument.

1.3 Theory and Hypotheses Development

In this section, I develop testable hypotheses for my empirical analyses. I hypothesize that innovation success may act as a signal of a firm's research quality to the equity market, thus reducing the

[10] A working paper on intellectual property laws by Dass, Nanda, and Xiao (2015) show that stronger protection for trade secrets result in greater opacity and lower stock liquidity. In contrast to the above paper, I show that higher innovation success by firms leads to lower information asymmetry in the equity market. This, in turn, leads to lower leverage ratios and lower dividend payout ratios for such firms.

extent of information asymmetry facing the firm when it attempts to raise external finance in the equity market.[11] This reduction in information asymmetry, in turn, will affect the capital structure of the firm (equity rather than debt issues) and its dividend policy (dividend payout as a fraction of earnings).

First, I discuss how patents may convey information to the equity market (outside investors). Patents provide certification of firms' quality. Firms' insiders know the true quality and progress of their corresponding firms' research, but may not be able to fully convey this information credibly to outside investors by making public announcements. However, patents act as a credible mechanism through which firms convey the value and progress of their research to outsiders. There are multiple arguments to support this view. First, the USPTO, an independent government agency, certifies firms' research by validating that it meets their criteria for patenting. Second, patenting is a costly process. There are direct and indirect costs associated with patents including R&D expenditures, patent application costs, patent maintenance costs, and potential litigation costs to protect patents. This means that a patent granted to a firm is not easy to mimic by a firm which has only lower quality research. In sum, equity market participants are likely to view a firm with a larger number of patents and higher quality patents as having greater intrinsic value, thus enabling them to act as credible signals of firm quality to the equity market. This means that firms with a larger number of patents and higher quality patents will face a smaller extent of information asymmetry in the equity market, which is the first hypothesis that I will test here (**H1**).

Next, I discuss how innovation success affects the capital structures of firms. On the one hand, innovation success may reduce the uncertainty faced by investors about a firm's prospects, i.e., firm riskiness. However, in a Modigliani and Miller (1958) world, i.e., in a setting with no market imperfections, a reduction only in a firm's riskiness will have no effect on its capital structure. On the other hand, as I argued earlier, innovation success may reduce the extent of information asymmetry faced by firms. Myers and Majluf (1984) show that, in a setting with information asymmetry, firms prefer debt over equity to raise external finance. However, debt has its own costs arising from various market imperfections such as the cost of financial distress associated with the extent of debt in the capital structure (see, e.g., Bradley, Jarrell, and Kim (1984) and Shyam-Sunder and Myers (1999)). Therefore, firms facing a smaller extent of information asymmetry in the equity

[11] Debt as a security is less sensitive to information asymmetry compared to equity.

market will have lower leverage ratios arrived at by trading off the costs associated with equity issues (which decreases with the reduction of information asymmetry facing the firm) against the financial distress costs that increase as firms' debt ratios increase.[12] Earlier, I hypothesized that firms with a higher quantity and quality of patents will face a smaller extent of information asymmetry in the equity market. Therefore, through the information asymmetry channel, I would expect firms with higher innovation success to have lower leverage ratios, which is the next hypothesis that I will test here (**H2**). Using similar arguments, firms with higher innovation success will have a greater propensity to issue equity rather than debt to raise external financing (**H3**).

Finally, I discuss how the reduction in information asymmetry caused by higher innovation success affects the dividend payout policies of firms. For dividends to serve as a credible signal, it must be costly for firms to pay out each dollar of dividend compared to retaining that amount for reinvesting in the firm.[13] This means that firms with a higher quantity and quality of patents, facing a lesser extent of information asymmetry in the equity market, need to signal only to a smaller extent, i.e., they will have lower dividend payout ratios in equilibrium. This is the next hypothesis that I test here **(H4)**.

1.4 Institutional Background: The Patent Application Process

Patent applications are filed with the USPTO. A patent application is first sent to the Office of Initial Patent Examination (OIPE), which performs initial processing to ensure that the application is in condition for examination.[14] The OIPE collects the application fees, assigns a serial number to the application, and reviews it for other formalities. It also checks for specification (written description along with citations), list of claims made by the applicant, and other oaths and declarations made by the applicant. After the initial review, the application is assigned a filing date, class, and art-unit. Each art-unit pertains to patents in a specific field, e.g., art-unit 2783 pertains

[12] Of course, there may be other factors affecting a firm's capital structure choice such as the tax benefit of debt. My hypotheses hold regardless of the various market imperfections driving its optimal capital structure choice. *Ceteris Paribus*, a reduction in information asymmetry will tilt a firm's capital structure toward greater equity issuance (and, correspondingly, lower leverage ratio).

[13] For example, in Miller and Rock (1985), the cost of paying dividends is foregoing investment in a firm's projects, i.e., the cost of underinvestment. In John and Willimas (1985), the cost is higher tax rate on dividends compared to capital gains tax.

[14] See, e.g., the following link for more details on patent application process: https://www.uspto.gov/patent/office-patent-application-processing.

to electrical computers and digital processing systems. The supervisory patent examiner (SPE) of an art-unit assigns the application to a patent examiner for review. In my sample, there are 13,250 different examiners over the years, 746 art-units, and 475 technology classes.

Lemley and Sampat (2012) conducted interviews with around two dozen patent examiners and SPEs and found that, for some art-units, SPEs assigned applications to particular examiners on the basis of the last digit of the application number, whereas, in some art-units oldest unassigned application is assigned to an examiner who has just finished examining another application. Therefore, conditional on application year and technology type, we can consider the assignment of applications to patent examiner as effectively random.[15] Upon receiving an application, an examiner evaluates the patentability of application by checking whether it is unique, non-obvious, useful, clearly described, and has definite claims. If the application meets all these criteria it is eventually accepted; otherwise it is rejected. Technically, patent applications are never rejected, and the prior literature considers all the abandoned applications as rejected. Finally, the USPTO publishes issued patents and most patent applications (including rejected applications) eighteen months from the earliest effective application filing date, and makes various other publications concerning patents.

Additionally, patents are costly to obtain and maintain. First, firms spend considerable amounts on R&D and human resources (e.g., inventors). Second, as Lemley (2000) states that on average, patent applications cost upwards of $20,000 including application and attorney fees spanning the application process. Additionally, applicant must pay maintenance fees on their patents to prevent it from expiring before its term, which is usually 20 years from filing. Finally, there are indirect costs associated with patents. For example, patent litigation may potentially be very costly. As per the American Intellectual Property Law Association, the cost of an average patent lawsuit, where $1 million to $25 million is at risk, is $1.6 million through the end of discovery and $2.8 million through final disposition.[16]

[15] See, e.g., Sampat and Williams (2019) for more details.

[16] See, e.g., this link for more details on patent litigation: https://www.ipwatchdog.com/2013/02/05/managing-costs-of-patent-litigation/id=34808/

1.5 Data, Sample Selection, and Innovation Success Measures

1.5.1 Sample Selection

I obtain the data for my analyses from multiple databases. The sample of the U.S. public firms and their respective financial information comes from the Compustat annual database. My sample period begins in 1981 and ends in 2016. I drop all financial firms (all firms with SIC codes between 6000 and 6999), utility firms (SIC codes between 4900 and 4999), and foreign firms. I remove observations with missing or zero total book assets and observations having negative total debt. I obtain information asymmetry data for the period of 1981 to 2016 from the IBES database, which tracks the analyst coverage of public firms. Since IBES data is available from 1981 onward, I begin my Compustat sample from 1981. I use the 2006 edition of NBER Patent Citation database (see, e.g., Hall, Jaffe, and Trajtenberg (2001) for details) for information on patent grants and their respective forward citations. I augment this dataset using patent data from the Harvard Patent Network Dataverse, which contains patent and citation information through 2010. I also use the patent data set created by KPSS (2017) for the purpose of matching patents to the public firms in my sample. The KPSS dataset matches patents to public firms in the Center for Research in Security Prices (CRSP) database. I use the "Patent Number" and "Permno" match from this dataset to match patents in my sample to the Compustat database. I obtain the permno of Compustat firms in my sample using the CRSP/Compustat merged dataset. I augment this matched data using additional USPTO data. I download weekly published patent grant files from the USPTO website to obtain patents and citations data from 2011 to 2015. I collate all the weekly USPTO extended markup-language (XML) files from 2011 to 2015 and parse them to collect patents and citations information. I match these patents to Compustat firms by applying the matching procedure used by Bernstein, Giroud, and Townsend (2016). My final sample of patent data comprises all patents applied (and eventually granted) from 1976 to 2015. I restrict the sample to 2013 to address the truncation issues with patent dataset along with other measures to address truncation as described in detail in Section 5.2. Following the literature, I assign a value of zero to patent stocks of firms if such firms do not have any patents. The final sample consists of 186,122 firm-year observations.

For my identification strategy (IV analyses), I collect the patent applications data from the publicly available USPTO Patent Application Information Retrieval (PAIR) database. For each application, PAIR contains information on filing date, patent class and subclass, current application status, examiner name, examiner ID, and the corresponding art unit. I retrieve all the patent applications between 2001 and 2016 from the PAIR database. My sample begins in 2001 since the implementation of the American Inventors Protection Act (AIPA), effective on 29th November, 2000, made it mandatory to publish almost all patent applications irrespective of the outcome of the application.[17] PAIR, however, does not contain information on firms on whose behalf inventors have filed patents. Thus, I use the USPTO Patent Assignment dataset to identify firms which are the ultimate owners of patents. I use the name matching algorithm used by Bernstein, Giroud, and Townsend (2016) to match the Compustat firm names to assignee names in the merged PAIR/USPTO Patent Assignment dataset. For my IV analyses, I restrict my sample to firms that have filed at least one patent application in a rolling three-year period. I restrict my sample to 2014 to account for the lag between patent applications and grants. I describe my IV analyses in detail in the next section. The final sample for my IV analyses consists of 28,974 firm-year observations.

1.5.2 Measures of Innovation Success

I use both patents and citations data to construct my innovation success measures. Empirical evidence show that forward citations are strong signals of the economic value of patents (Hall, Jaffe, and Trajtenberg (2005) and KPSS (2017)).

Patent data are subject to two types of truncation problems. First, patents are included in the dataset only after they are granted, and on average, there is a two to three year lag between patent application and the respective grant. Thus, in the last few years of my sample I observe a lower number of granted patents. Following Seru (2014), I address this problem by dividing each patent of a firm in a filing year by the mean number of patents for all firms for that year having the same 3-digit technology class as the patent. The second type of truncation problem pertains to the citation count. For a given patent, I count the total number of citations received from the grant year until 2015 (i.e., forward citations). Patents tend to receive citations over a long period, but not much during the initial years after their grant. As a result, citation counts of later-year patents in my sample may be downward biased. For example, on average, patents filed in 2010 will

[17] Graham, Marco, and Miller (2015) show that PAIR has a good coverage of utility patent application filings since 2001 with 95% of applications between 2001 and 2012 covered in the PAIR database.

have fewer citations than those filed in 2003. I address this bias by scaling the citations of a given patent by the total number of citations received by all patents filed in that year in the same 3-digit technology class as the patent (Seru (2014)). Thus, I create class-adjusted (i.e., cohort-adjusted) measures of patents and citations, adjusted for trends in innovation activity in their respective USPTO specified technology classes. Lastly, following Lerner and Seru (2017), I restrict my sample to 2013, two years before 2015, to further address any remaining concerns of truncation bias.[18]

For each firm, I calculate the stock of patents on a yearly basis. Following Bloom and Van Reenen (2002), I calculate the stock of patents using the perpetual inventory method with a depreciation rate δ, of 30%.[19] Thus, for a firm i in year t, I calculate the stock of patents in the following way:

$$\textit{Patent Stock}_{i,t} = \textit{Patents Granted}_{i,t} + (1-\delta)\textit{Patent Stock}_{i,t-1}, \tag{1.1}$$

$$\textit{Citation Stock}_{i,t} = \textit{Citations Received}_{i,t} + (1-\delta)\textit{Citation Stock}_{i,t-1}. \tag{1.2}$$

In equation (1), $\textit{Patent Stock}_{i,t}$ is the stock of class-adjusted patents of a firm i in year t, and $\textit{Patents Granted}_{i,t}$ is the number of patents granted in year t by firm i. Likewise, in equation (2), $\textit{Citation Stock}_{i,t}$ is the stock of citations of a firm i in year t, and $\textit{Citations Received}_{i,t}$ is the sum of class-adjusted forward citations received on the patents granted in year t to firm i. Here, δ is the depreciation rate. Using the stock of patents and forward citations, I construct two measures of innovation success. All measures are based on the grant years of patents.[20] The first measure, *Ln(1+Stock of Patents)*, is the natural logarithm of one plus the class-adjusted stock of patents for a particular firm for a given year. The second measure *Log(1+Stock of Citations/Patent)* is the natural logarithm of one plus the ratio of class-adjusted stock of citations and the class-adjusted stock of patents. I take the natural logarithm because the distribution of patents and citations are skewed. I add one to the actual values to avoid losing observations having zero patents and citations. Panel A of Table 1 reports the summary statistics for my two innovation success measures.

[18]My results are robust to considering the entire sample and also restricting my sample to different time periods.
[19]Results are robust to using different depreciation rates.
[20]My results are robust to computing these innovation success measures as of the patents' application years.

1.5.3 Summary Statistics

My sample consists of all non-financial and non-utility firms in the Compustat dataset from 1981 to 2013. Panel A of Table 1 shows the summary statistics of key dependent and independent variables for these firms. I winsorize all variables at 1% and 99%. The median firm in my sample has profitability and asset tangibility ratios of 0.09 and 0.21, respectively. The average value of class-adjusted patent and citation measures in my samples are 0.49 and 0.003, respectively. I discuss the construction of my dependent variable, including information asymmetry measures (namely, analyst coverage, analyst forecast error, and analyst dispersion), in Section 7.1 with my empirical specification.[21]

Panel B of Table 1 reports the summary statistics of the patent applications and examiners. A median firm makes 5 patent applications over a three-year period and receives 3 patent grants on those applications. The average success rate of application is around 72%. I also report average examiner leniency computed at the firm level in this panel. I describe the details of constructing this measure in the next subsection. Finally, I show the annual art-unit-adjusted examiner leniency for all examiners in my sample.

Panel C of Table 1 reports the summary statistics of the other measures of innovation success that I use for my robustness tests. I use the natural logarithm of dollar values of patents granted to firms over a year normalized by the book value of assets and the natural logarithm of class-adjusted forward citations to patents granted to a firm over a year normalized by the book value of assets (following KPSS 2017) as two additional measures of innovation success. I describe the construction of these measures in the section on robustness tests.

1.6 Identification Strategy: IV Analyses

As mentioned, my baseline analyses may suffer from some endogeneity concerns. It may be argued that my results are driven by some omitted variable bias. For example, higher quality firms may have greater innovation success while at the same time, have cheaper access to the equity. To

[21] I assign a value of zero to the analyst coverage if a firm is not followed by analysts. However, analyst forecast error and analyst dispersion can only be computed for firms having non-zero analyst coverage. This is why the number of observations differ for the variable analyst coverage, compared to the number of observations for forecast error and analyst dispersion.

address potential endogeneity concerns, I use IV analyses as my identification strategy. Specifically, I instrument the number of patents granted to a firm using a measure of examiner leniency, which I describe in detail in the following subsection. My IV analyses rely on the random assignment of patent applications to patent examiners within a given art-unit and exogenous variation of examiners' leniency in approving patent applications. Prior literature suggests that the patent-review process leaves significant discretion in the hands of examiners. Thus, I exploit the differences in leniency across examiners and the random assignment of applications to examiners (conditional on technology and year) for identification.

As described, a patent application is assigned in an art-unit for review based on the technology field of the application. Art-units consist of several patent examiners, who specialize in a narrow technology field, i.e., within their respective art-units. USPTO assigns an application number, patent class, and subclass to each patent application and sends it to the relevant art-unit for review. Within an art-unit, applications are randomly assigned to examiners. My quasi-experimental approach builds on similar applications from the literature. Maestas, Mullen, and Strand (2013) exploit the variation in the allowance rate of disability insurance examiners to show the disincentive effect of benefits. Sampat and Williams (2019), Farre-Mensa, Hegde, and Ljungqvist (2019), and Gaule (2018) use patent examiners' leniency as an instrument in their research. I now describe my instrument in detail.

1.6.1 Instrument: Average Examiner Leniency

I compute time-varying measures of examiner's leniency as follows:

$$Examiner\ Leniency_{aijkt} = \frac{Grants_{jkt} - 1(Grant_a = 1)}{Applications_{jkt} - 1}, \tag{1.3}$$

$$Art\text{-}unit\ Leniency_{aikt} = \frac{Grants_{kt} - 1(Grant_a = 1)}{Applications_{kt} - 1}, \tag{1.4}$$

where $Examiner\ Leniency_{aijkt}$ is the yearly approval rate of examiner j, affiliated to art-unit k and assigned to review patent application a filed by firm i in the year t. $Grants_{jkt}$ and $Applications_{jkt}$ are the total numbers of patents granted and applications reviewed, respectively, by examiner j in the same application year t. $Art\text{-}unit\ Leniency_{aikt}$ is the approval rate of art-unit k, as a whole, assigned to review patent application a filed by the firm i in the year t. $Grants_{kt}$ and $Applications_{kt}$ are the total numbers of patents granted and applications reviewed, respectively, by all examiners in the art-unit k in the same application year t. Intuitively, the empirical setup follows prior research that leaves out the application itself while computing examiner approval rate.[22]

Individual examiners within an art unit differ in their tendency of accepting or rejecting patent applications. Lemley and Sampat (2012) and Sampat and Williams (2019) show that patent applications assigned to lenient and strict examiner are similar on observable characteristics. Given that I am interested in obtaining an instrument for the number of patents eventually granted to a firm, I average examiners' leniency across all its patent applications. I adjust individual examiner's leniency by art-unit's overall leniency to capture the variation in leniency within an art-unit. By computing the annual art-unit adjusted measures of examiner leniency, I account for the art-unit and the year specific effects, which may drive the grant rate for patent applications in a particular technology and in a given year. For any firm in a particular year, I consider all patent applications filed by the firm over a rolling three-year window. Further, I restrict my sample to firms having filed at least one patent application in a rolling three-year period. A median firm makes 5 patent applications during the three-year period, as described in the summary statistics subsection.[23]

I compute the average examiner leniency for a firm using the following specification:

$$Adjusted\ Examiner\ Leniency_{it} = \frac{1}{n_i}\sum_{a=1}^{n_i}(Examiner\ Leniency_{aijkt} - Art\text{-}unit\ Leniency_{aikt}). \quad (1.5)$$

$Adjusted\ Examiner\ Leniency_{it}$ is the average of art-unit adjusted examiners' leniency for a firm i and n_i is the number of patent applications filed by the firm i during the three-year window. My study averages examiners' leniency at the firm level, allowing me to obtain an instrument for the stock of patents eventually granted to the firm.[24] Figure 1 shows the variation of art-unit adjusted examiners' leniency per year across the sample period (obtained by subtracting eq(4) from eq(3)).

[22] I use yearly measures of examiner leniency since examiners, on average, become more lenient with experience implying a within-examiner change in leniency over time (Lemley and Sampat (2012)). This approach also helps me account for year specific effects on patent application process.

[23] I choose a three-year window to analyze the number of patent applications by a firm, since a patent application, on average, takes two to three years before acceptance. Thus, mechanically my instrument should not capture the modification and resubmission of a rejected application by a firm to get a lenient examiner. I also show that there is no correlation between the current average examiner leniency and the number of patent applications filed by a firm in the future, which also rules out the above concern. Additionally, my results are also robust to computing the average leniency over two-year and four-year windows.

[24] I use the average examiner leniency across multiple applications as an instrument rather than the leniency of the examiner reviewing the first patent application filed by a firm, since a firm may apply for multiple patents, and all of them may be important for conveying information about the firm's research.

I run two-stage least squares regressions (2 SLS) as follows:

$$\textit{Ln(1+No. of Patents)}_{it} = \alpha_1 \textit{Average Examiner Leniency}_{it} + \alpha_2 \textit{Applications}_{it} + \alpha_3 X_{it} + \epsilon_{it}, \tag{1.6}$$

$$\textit{Outcome}_{i,t+1} = \beta_1 \textit{Predicted Ln(1+No. of Patents)}_{it} + \beta_2 \textit{Applications}_{it} + \beta_3 X_{it} + \epsilon_{i,t+1}. \tag{1.7}$$

Equation (6) represents the first stage of my 2SLS model where I regress $\textit{Ln(1+No. of Patents)}_{it}$ on the average art-unit adjusted examiners' leniency computed for firm *i*. $\textit{Ln(1+No. of Patents)}_{it}$ measures the natural logarithm of one plus the total number of patent eventually granted to a firm during a rolling three-year window. $\textit{Applications}_{it}$ is the number of applications filed by the firm in a rolling three-year window and X_{it} is a vector of relevant controls, which I use for my baseline regressions.[25] Equation (7) represents the second stage of my 2SLS model, where I regress different firm outcomes ($\textit{Outcome}_{i,t+1}$) on the predicted value of the natural logarithm of one plus the total number of granted patents calculated from the first stage.[26] My controls and fixed effects remain consistent for the two stages. My sample period runs from 2001 to 2014.[27]

My instrument, average examiner leniency, satisfies both the relevance condition and the exclusion restriction. First, average examiner leniency is a strong predictor of number of patents granted to a firm, controlling for the number of patent applications and other firm observables. The Cragg-Donald Wald F statistics of the first-stage of my 2 SLS regressions exceed the critical value of 10 (Stock and Yogo (2002)). The coefficients of the instrument in the first-stages of all my results are positive (as predicted) and highly significant at the 1% level as shown in Tables 3, 5, 8, and 10. These results suggest that my instrument is relevant. Second, prior literature has provided arguments about the random assignment of patent applications to patent examiners.[28] In Section

[25] My IV results hold even if I do not control for the number of patent applications filed by firms. However, controlling for applications is appropriate, because both the number of applications and examiner leniency affect the number of patents granted to a firm. Futher, there is no discernible change in point estimates using either approach.

[26] To ensure that my results are not driven by examiners who examine a small number of applications during a year, I restrict my sample to those examiners who examined at least 10 applications in a year. Further, I restrict my sample to art-units having at least two examiners in a year. My results are robust to using the full sample without any restrictions.

[27] I restrict my analyses to 2014, because there is a two to three year lag between patent applications and patent grants. My results are also robust to censoring my sample to different periods.

[28] In an untabulated analysis, I conduct the random assignment test suggested by Righi and Simcoe (2019). My instrument passes their validation test. Similar to Farre-Mensa, Hegde, and Ljungqvist (2019) and Sampat and Williams (2019), I show that the coefficient of examiner leniency upon regressing patent application outcomes on

4, I describe in detail the patent application process and relevant literature, which argues that, conditional on technology and application year, patent applications are randomly assigned to patent examiners. Additionally, patent applicants are not aware of the identity of patent examiners at the time of application.[29] Additionally, as shown in Table A-2 of the appendix, my instrument, average examiner leniency, is uncorrelated to observable firm characteristics, such as size, age, market to book, profitability, number of patent applications, and R&D expenditure. Thus, it may be argued that the only channel through which average examiner leniency affects firm outcomes is through the number of patent granted to a firm, satisfying the exclusion restriction.

1.7 The Effect of Innovation Success on Information Asymmetry

In this section, I show the empirical specifications, and the results of my baseline and IV analyses of the effect of innovation success on information asymmetry.

1.7.1 Baseline Analysis

I expect firms with higher innovation success to have a smaller extent of information asymmetry in the equity market. In this section, I empirically test this hypothesis **H1**. I construct standard measures of information asymmetry following the literature (Christie (1987), Behn, Choi, and Kang (2008), and Krishnaswami and Subramaniam (1999)). I obtain analysts' forecasts on individual firms from the IBES database. Specifically, for each public firm and each year, I retrieve sell-side analysts' earnings forecasts within one year of the annual earnings announcement date. I employ three measures of information asymmetry. The first measure is the natural logarithm of one plus the total number of analysts covering the firm (*Ln(1+#Analysts)*) during a period of one year prior to earnings announcement. If a firm is not followed by analysts during a year, I assign a value of zero to the analyst coverage variable. Second, I use the standard deviation of analysts' forecasts scaled by the price per share (*Analyst Dispersion*) as the second measure of information

patent examiner leniency and controls does not change, whether I include the technology-subclass by year fixed effects or use the art-unit by year fixed effects.

[29] One may be concerned about the use of average examiner leniency as an instrument, since it may have an impact on the future number of patent applications filed by a firm. However, in Table A-1 in the appendix, I show that this is not the case: I do not find any correlation between the average examiner leniency of a firm and its subsequent patent applications in the following periods. This test rules out the concern that firms are resubmitting rejected patent applications to get lenient examiners. Additionally, in Table A-2, I show that the average examiner leniency is uncorrelated to observable firm characteristics.

asymmetry. My final measure of information asymmetry is the mean-squared error of analysts' forecasts (*Forecast Error*). I measure the mean-squared error as the absolute difference between average earnings forecast and the actual earnings per share divided by the price per share at the end of a fiscal year.[30] These are common measures of information asymmetry used in the corporate finance literature with the following implications.

Firms facing lower information asymmetry have greater analyst coverage, lower analyst dispersion, and lower forecast error. I control for a firm's size (*Ln(Total Assets)*) and its age (*Ln(Age)*), because larger and older firms are expected to have smaller extent of information asymmetry. I also control for (*Market to book*). Additionally, I also control for innovation input using the ratio of R&D expenses to the book value of assets of firms (*R&D Expenditure*). Following the prior literature, I set the missing R&D expenditure observations to zero.[31] The main independent variables of interest are the two innovation success measures. I use two-digit SIC industry fixed effects and year fixed effects in all regressions to account for any industry related heterogeneity or year-specific shocks. I cluster standard errors at the firm level because of the persistence of firms' financial policies. Thus, I estimate the following model:

$$Information\ Asymmetry_{i,t+1} = \alpha_0 + \alpha_1 Innovation_{i,t} + X_{i,t} + Industry\ FE + \ Year\ FE + \epsilon_{i,t+1}, \tag{1.8}$$

where i indexes firm and t indexes time. $Information\ Asymmetry_{i,t+1}$ represents the three measures of information asymmetry. Here, $Innovation_{i,t}$ are the two innovation success measures described in the previous section. $X_{i,t}$ represents the vector of controls. All independent variables are lagged by one year.

Table 2 reports the baseline results. In Columns (1) to (3), coefficients of the log measure of the stock of patents are significant at the 1% level, implying that innovation success increases analyst coverage and reduces standard deviation (dispersion) of analyst forecasts and mean analyst forecast errors. In Column (4) to (6), coefficients of the log measure of the stock of citations per patent are significant at the 1% level.[32] My results are also economically significant. A one standard deviation

[30] Additionally, I also require that a firm be followed by at least five analysts for the purpose of computing dispersion and forecast errors following Bae, Stulz, and Tan (2008).

[31] My results are robust to not replacing missing R&D expenditure values with zero.

[32] In an untabulated analysis, I show that firms with higher quantity and quality of patents have lower probability

increase in the log measure of the stock of patents leads to a 13.2 percentage point increase in the log number of analysts following a firm, implying a 16.1% greater value of the average analyst following. A one standard deviation increase in the log measure of the stock of patents leads to a 22.1% decrease in the average value of analyst dispersion and a 24.7% decrease in the average value of analyst forecast error. The findings in this section supports my hypothesis **H1** that firms having a higher quantity and quality of innovation success will face a smaller extent of information asymmetry in the equity market.

1.7.2 IV Analysis

I conduct an IV analysis to establish that my baseline results are causal. I run a 2SLS model with the first-stage the same as the equation (6). The second-stage is based on the equation (7) with $Outcome_{i,t+1}$ representing the log number of analysts, analyst dispersion, and analyst forecast error, which are the information asymmetry measures. I use the exact controls and fixed effects as I did in my corresponding baseline analysis while controlling for the number of applications ($Applications_{it}$). I control for the number of applications, because, all else equal, firms having a higher number of applications are likely to have a higher number of patents. In my empirical specification, results are driven by the exogenous variation of average examiner leniency faced by a firm. Since I compute yearly measures of art-unit-adjusted examiner leniency, I cluster standard errors at calendar-year level.

Table 3 shows the IV regression results. In Columns (1) and (3), I show the first stages of my IV analysis. I observe that the coefficients of average adjusted examiner's leniency measure (*Examiner Leniency*) are positive and highly significant at the 1% level. In Columns (1) and (3), first-stage Cragg-Donald F statistics are 118.151 and 51.222, exceeding the critical value of 10 (Stock and Yogo (2002)). The predicted value of patents obtained from the first stage is the main independent variable of interest of the second stage regressions. I show the second-stage results in the following columns. In Column (2), the dependent variable is the log number of analysts, and the predicted value of patents has a positive, but insignificant impact on the analyst coverage. In Column (4), the dependent variable is the analyst forecast dispersion and, the estimated patent measure has a

of informed (PIN) trading using the PIN measure of Easley, Kiefer, and O'Hara (1997). This result also shows that firms with higher quantity and quality of patents are associated with lower information asymmetry in the equity market.

negative and significant (10% level) impact. In Column (5), I use the mean forecast error as the dependent variable, and the estimated patent measure has a negative and significant (10% level) impact.[33] These results support the hypothesis **H1** that firms' innovation success leads to a smaller extent of information asymmetry facing them in the equity market.

1.8 The Effect of Innovation Success on Firms' Capital Structures

In this section, I show the results of my baseline and IV analyses of the effect of innovation success on capital structure.

1.8.1 Leverage Ratios: Baseline Analysis

I empirically test my hypothesis **H2**, which states that firms having a higher quantity and quality of patents will have lower leverage ratios. I construct the standard measures of capital structure, namely, book leverage and market leverage. *Book Leverage* is defined as the ratio of long-term debt plus debt in current liabilities to the book value of total asset. *Market Leverage* is defined as the ratio of long-term debt plus debt in current liabilities to the market value of total asset. The market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and share price. I use the standard controls in the capital structure literature including asset tangibility (*Tangible Asset*), investment opportunity (*Market to Book*), profitability (*Profitability*), and size (*Log (Sales)*), following Rajan and Zingales (1995). I control for innovation input using the ratio of R&D expenditure to the book value of assets of firms (*R&D Expenditure*). I also control for firms' age (*Ln(Age)*) and whether firms pays dividends, (*Dividend Paying Dummy*). The main independent variables of interest are the two innovation success measures. I use two-digit SIC industry fixed effects and year fixed effects in all regressions. I cluster standard errors at the firm level. Thus, I estimate the following model:

$$Leverage_{i,t+1} = \alpha_0 + \alpha_1 Innovation_{i,t} + X_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t+1}, \qquad (1.9)$$

[33] My IV analysis has a smaller sample size than my baseline analysis, since I only considers firms with at least one patent application in a 3-year rolling period. My baseline analysis hold, when conducted in the subsample of firms considered in my IV analysis.

where i indexes firm and t indexes time. $Leverage_{i,t+1}$ represents book and market leverage. $Innovation_{i,t}$ represents the two innovation success measures described in the earlier section. $X_{i,t}$ represents the vector of controls. All independent variables are lagged by one year.

Table 4 reports the baseline results. All innovation success coefficients are statistically significant (1% level) for both book and market leverage tests. The results are also economically significant. A one standard deviation increase in the log measure of the stock of patents leads to a 1 percentage point decrease in the *Book Leverage* for the next year, which is equivalent to a 4.5% decrease in the average value of *Book Leverage*. Further, a one standard deviation increase in the log measure of the stock of patents leads to a 1.6 percentage point decrease in the *Market Leverage* for the next year, which is equivalent to a 9.7% decrease in the average value of *Market Leverage*. These results suggest that innovation success leads to lower leverage ratios for firms, supporting my hypothesis **H2**.

1.8.2 Leverage Ratios: IV Analysis

I conduct an IV analysis to establish that my baseline results are causal. I use the exact controls and fixed effects as I did in my corresponding baseline analysis while controlling for the number of applications ($Applications_{it}$).[34] I cluster standard errors at calendar-year level.

Table 5 shows the IV regression results. In Column (1), I show the first stage of my IV analysis. I observe that the coefficient of average adjusted examiner's leniency measure (*Examiner Leniency*) is positive and highly significant at the 1% level. The first-stage Cragg-Donald F statistic is 105.739. I show the second stage results in the following columns. In Columns (2) and (3), dependent variables are the book and market leverage, respectively. The coefficient of estimated patent measure is negative and significant at the 5% level in Column (2) for the book leverage. In Column (3), the coefficient is insignificant, but in the right direction. My IV results support my hypothesis **H2** that firms with higher innovation success have lower leverage ratios.

[34] In an untabulated analysis, my IV results hold with firm fixed effects. My baseline results are weaker with firm fixed effects. This is expected, since it has been argued in the literature that firm's capital structure is time invariant and that most of the variation in capital structure is across firms.

1.8.3 The Impact of Information Asymmetry on the Capital Structures of Firms: Direct Tests

I establish that innovation success affects the capital structure through the information asymmetry channel. I use information asymmetry variables as controls in my baseline regressions on capital structure, using innovation success measures as the main independent variables.

Table 6 report the results of these regressions. Panel A shows the results for book and market leverage ratios and use analyst coverage as a measure of information asymmetry. Consistent with my expectation, I show that the coefficients of analyst coverage are negative and significant at 1% levels in all four columns. This means that firms with greater analyst coverage (lower information asymmetry) have lower leverage ratios. Further, the coefficients of the stock of patents and the stock of citations per patent, are still negative and significant. However, the coefficients of the stock of patents and the stock of citations per patent are smaller in magnitude compared to the coefficients from regression in which the information asymmetry variable (analyst coverage) is not included (i.e., compared to Table 4 results), suggesting that the effect of innovation success on capital structure is through the information asymmetry channel. In Panel B, I show that the coefficients of analyst dispersion and forecast error are positive and significant. This implies that firms with lower analyst dispersion and lower forecast error, i.e., lower information asymmetry, have lower leverage ratios. This test provides the direct evidence that innovation success affects the capital structures of firms through the information asymmetry channel, and also provides the direct evidence of the impact of information asymmetry on capital structure.[35]

1.8.4 Equity versus Debt Issues: Baseline Analysis

I expect that firms with a higher quantity and quality of patents will issue equity rather than debt (hypothesis **H3**). Following Chang, Dasgupta, and Hillary (2006), I construct a measure of equity over debt issue. I define a dummy variable that takes the value one if a firm issues net equity in a year and zero if the firm issues net debt. Net equity issue is defined as the ratio of the sale of common and preferred equity minus the purchase of common and preferred equity in a given year

[35] Due to space restrictions, I provide additional evidence in the appendix that shows the direct impact of information asymmetry on the capital structure and dividend payout ratios of firms. In Tables A5 and A6 in my appendix, I show that firms with lower information asymmetry have lower leverage ratios and lower dividend payout ratios.

scaled by the book value of assets at the beginning of the year. Net debt is defined as the ratio of the long-term debt issuance in a given year minus the long-term debt reduction in the year plus the change in current debt in a given year scaled by the book value of the assets at the beginning of the fiscal year. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by book value of assets exceeds 5%.[36] Observations where firms issue both equity and debt in a given fiscal year are dropped. I use the same set of controls used in tests on book and market leverage. I include asset tangibility (*Tangible Asset*), investment opportunity (*Market to Book*), profitability (*Profitability*), size (*Ln(Sales)*), *Dividend Payer Dummy*, and age *(Ln(Age))* as controls following Chang, Dasgupta, and Hillary (2006) and Hovakimian, Opler, and Titman (2001). I also control for innovation input using the ratio of R&D expenditure to the book value of assets of firms (*R&D Expenditure*). I use a probit regression model to establish the effect of innovation success on equity rather than debt issues by firms.[37] The main independent variables of interest are the two innovation success measures. I use two-digit SIC industry fixed effects and year fixed effects. I cluster standard errors at the firm level. I estimate the following model:

$$Pr[Issue{=}1]_{i,t+1} = \alpha_0 + \alpha_1 Innovation_{i,t} + X_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t+1}, \qquad (1.10)$$

where i indexes firm and t indexes time. *Issue* is a dummy variable, which takes the value one if a firm issues equity in the year and zero if the firm issues debt. $Innovation_{i,t}$ represents the two innovation success measures described in the previous section. $X_{i,t}$ represents the vector of controls. All independent variables are lagged by one year.

Table 7 reports regression estimates of the probit regression. I show the marginal effect of all independent variables in this table. In Columns (1) and (2), the log measure of the stock of patents and the log measure of the stock of citations per patent have positive and significant (1% level) effects, implying that firms with higher innovation success issue equity rather than debt to raise external finance.[38] Again, my results are economically significant. A one standard deviation increase in the log measure of the stock of patents leads to a 4.4 percentage point increase in

[36] Results are robust to considering cases when the net equity (debt) issued divided by total book assets exceeds 1%.

[37] The results are robust to using a linear probability model, which I show in Table A3 in the appendix.

[38] In an untabulated analysis, I also show that firms with higher quantity and quality of patents have higher algebraic announcement effect to equity issues. This implies that firms with higher quantity and quality of patents have lower cost of issuing equity.

the probability of issuing equity over debt, which is equivalent to a 9.9% increase in the average probability of issuance of equity rather than debt. These results imply that firms with higher innovation success have a greater propensity to issue equity rather than debt, which validates my hypothesis **H3**.

1.8.5 Equity versus Debt Issues: IV Analysis

I conduct an IV analysis to establish that my baseline probit results are causal. I use the exact controls and fixed effects as I did in my corresponding baseline probit regressions while controlling for the number of applications ($Applications_{it}$). I cluster standard errors at calendar-year level.

Table 8 shows the IV regression results. I show the marginal effect of all independent variables in this table. In Column (1), I show the first stage of my IV analysis. I observe that the coefficient of average adjusted examiner's leniency measure (*Examiner Leniency*) is positive and highly significant at the 1% level. The first-stage Cragg-Donald F statistic is 58.439. I show the second-stage results in the following column. In Column (2), where I show the second-stage results for the probit model with IV regressions, estimated patent measure has a positive and significant (1% level) impact on the equity versus debt issue dummy variable. My IV results support the hypothesis **H3** that firms having higher innovation success have a greater propensity to issue equity rather than debt for external financing.

1.9 The Effect of Firms' Innovation Success on their Dividend Policies

In this section, I show the results of my baseline and IV analyses of the effect of innovation success on dividend payout ratios.

1.9.1 Baseline Analysis

I expect that firms with a higher quality and quantity of patents will have lower dividend payout ratios. In this section, I empirically test this hypothesis **H4**. Following Chemmanur, Paeglis, and Simonayan (2009), I define dividend payout as the ratio of the sum of common and preferred dividend to earnings before depreciation, interest, and taxes. I drop firm-year observations having positive dividends and negative earnings. I control for profitability (*profitability*), size (*Ln(Sales)*), *Cash Flow Volatility*, age (*Ln(Age)*), annual sales growth (*Sales Growth*), and cash holdings (*Cash/Asset*). I also control for innovation input using the ratio of R&D expenditure to the book value of assets of firms (*R&D Expenditure*). The main independent variables of interest are the two innovation measures. I use two-digit SIC industry fixed effects and year fixed effects in all regressions. I cluster standard errors at the firm level. I estimate the following model:

$$\textit{Dividend Payout}_{i,t+1} = \alpha_0 + \alpha_1 \textit{Innovation}_{i,t} + X_{i,t} + \textit{Industry FE} + \textit{Year FE} + \epsilon_{i,t+1}, \qquad (1.11)$$

where i indexes firm and t indexes time. $\textit{Dividend Payout}_{i,t+1}$ represents dividend payout ratios. $\textit{Innovation}_{i,t}$ represents the two innovation success measures described in the previous section. $X_{i,t}$ represents the vector of controls. All independent variables are lagged by one year.

Table 9 reports regression estimates. In Column (1), the log measure of the stock of patents has a negative coefficient, but it is insignificant. In Column (2), the log measure of the stock of citations per patent has a negative and significant coefficient at the 1% level. My results are economically significant.[39] A one standard deviation increase in the log measure of the stock of citations per patent leads to a 5.6% decrease in the mean dividend payout ratio. Thus, firms with higher innovation success have lower dividend payout ratios, supporting my hypothesis **H4**.

1.9.2 IV Analysis

I conduct an IV analysis to establish that my baseline results are causal. I use the exact controls and fixed effects as I did in my corresponding baseline analysis while controlling for the number of applications ($\textit{Applications}_{it}$). I cluster standard errors at calendar-year level.

Table 10 shows the IV regression results. In Column (1), I show the first-stage of my IV analysis. I observe that the coefficient of average adjusted examiner's leniency measure (*Examiner Leniency*) is positive and highly significant at 1%. The first-stage Cragg-Donald F statistic is 93.763. I show the second-stage results in the following column. In Column (2) estimated patent measure has a negative and significant (1% level) impact on dividend payout ratio.[40] My IV analysis results are in

[39] In an untabulated analysis, I show that firms with higher quantity and quality of patents have lower total payout ratio. I measure total payout ratio as the sum of net repurchase and dividend payout scaled by the earnings of firms following Floyd, Li, and Skinner (2015).

[40] Results are robust to using dividend per share as another proxy for the dividend payout.

the same direction as the baseline analysis and supports the hypothesis **H4** that firms with higher innovation success have lower dividend payout ratios.

My IV analyses establish that patents causally affect the financial policies of firms. The coefficients of my IV estimates are larger in magnitude than OLS estimates. One potential explanation is that very high-quality firms may have favorable perceptions in the equity market irrespective of outcomes of their patent applications and vice-versa for very low-quality firms. The outcomes of medium-quality firms may get affected significantly by the acceptance or rejection of patent applications. My instrument identifies the local average treatment effect (LATE) on the set of medium quality firms. Thus, the LATE in my IV analyses dominates the average treatment effect (ATE) and any potential omitted variable bias in my OLS analyses.

1.10 Robustness and Cross-sectional Analyses

For my robustness tests, I use two other measures of innovation success. First, I use the market value of patents measured by KPSS (2017). They study the stock market responses to patent grant announcements to capture the economic value of patents. Specifically, they measure a firm's market-adjusted abnormal return over the three-day window around the date of a patent approval and multiply it by the firm's market capitalization on the day prior to the approval to arrive at the dollar value of patents. Further, they sum the dollar value of all patents issued to a firm in a given year and normalize it by the book value of the firm's assets. They also found in their analyses that market values of patents are positively correlated with forward citations received by these patents. Second, I use the class-adjusted citations normalized by the book value of assets as my second alternative measure of innovation success from KPSS (2017).

In my robustness tests, I restrict the sample to firm-year observations in which firms are granted at least one patent, i.e., a sample of firms involved in some degree of innovation activity. My sample runs from 1981 to 2010, which includes the last year of the data provided by KPSS(2017). I use the natural logarithm of the sum of market values of all patents issued to a firm in a year scaled by the book value of assets of the firm as my first measure. Following KPSS (2017), I also use the natural logarithm of one plus the cohort-adjusted (class-adjusted) forward citations to all patents granted to a firm in a year scaled by the book value of assets of the firm as another measure of quality of innovation success. KPSS (2017) adjust the forward citations received on a patent by the average number of citations received by patents granted in the same year and in the same technological class as the patent in concern. As mentioned earlier, citations are a measure of quality of innovation success that captures the scientific value of patents. I use the natural logarithm when constructing the two variables, because distributions of both scaled variables are highly skewed. I next discuss the results of my robustness tests.

1.10.1 The Relationship between normalized measures of Innovation Success and Information Asymmetry

I test my hypothesis about the impact of innovation success on the extent of information asymmetry facing firms in the equity market (**H1**) by running OLS regressions using the above two measures of innovation success on a sample of firm-year observations with at least one patent granted during the year. In Table 11, *Ln(Dollar Value Patents/Assets)* is the natural logarithm of the total dollar value of all patents granted to a firm during a year scaled by the book value of assets of the firm. *Ln(Citation Weighted Patents/Assets)* is the natural logarithm of one plus cohort-adjusted forward citations to all patents granted to a firm in a year scaled by the book value of assets of the firm.

Table 11 shows the results of my analysis. In Columns (1) to (3), I use normalized dollar value of patents, and in Columns (4) to (6), I use class-adjusted citations, normalized by the book value of asset, as measures of innovation success. I show that firms having higher normalized dollar values of patent have higher analyst coverage (significant at 1% in Column (1)), lower analyst dispersion (significant at 5% in Column (2)), and lower analyst forecast error (significant at 5% in Column (3)). Next, I show that firms having higher normalized weighted citations have higher analyst coverage (significant at 1% in Column (4)), lower analyst dispersion (significant at 5% in Column (5)), and lower analyst forecast error (significant at 5% in Column (6)). These results suggest that firms having higher economic value and higher scientific value of innovation success face a smaller extent of information asymmetry in the equity market, supporting my hypothesis **H1**.

1.10.2 The Relationship between normalized measures of Innovation Success and Capital Structure

Next, I test my hypothesis on the capital structures of firms (**H2**) using the two scaled measures of innovation success defined above.

Table 12 shows the results of my analysis. In Columns (1) and (2), I use the normalized dollar value of patents and in Columns (3) to (4), I use class-adjusted citations normalized by the book value of assets as measures of innovation success. I show that firms having higher normalized dollar values of patent have lower book leverage (significant at 1% in Column (1)), and lower market leverage (significant at 1% in Column (2)). Next, I show that firms having higher normalized weighted citations have lower book leverage (significant at 1% in Column (3)), and lower market leverage (significant at 1% in Column (4)). These results suggest that firms having higher economic value and higher scientific value of innovation success have lower leverage ratios, supporting my hypothesis **H2**.

1.10.3 The Relationship between normalized measures of Innovation Success and Equity versus Debt Issues

Lastly, I test my hypothesis (**H3**) using the two scaled measures of innovation success defined above and the equity rather than debt issue as the dependent variable.

Table 13 shows the results of my analysis. I test my predictions using a probit model. I show the marginal effect of all independent variables in this table. In Column (1), I show that firms having higher normalized dollar values of patent have a greater propensity to issue equity over debt (significant at 1% level). Next, in Column (2), I show that firms with higher normalized weighted citations have a greater propensity to issue equity over debt (significant at 1% level). These results suggest that firms having higher economic value and higher scientific value of innovation success have a greater propensity to issue equity rather than debt to raise external finance, supporting my hypothesis **H3**.

1.10.4 Cross-Sectional Analyses of the Effect of Innovation Success on Capital Structure and Dividend Policies

I conduct cross-sectional analyses across firms facing lower versus higher information asymmetry and separately, across age groups of firms to provide additional evidence that innovation success affects the financial policies of firms through the information asymmetry channel. First, I show that the impact of innovation success on financial policies of firms is stronger for firms facing greater information asymmetry in the equity market, which is expected.[41] In Table A4 in the appendix, using interaction tests, I show that the same level of innovation success leads to lower leverage ratios for firms facing higher information asymmetry, i.e., firms having lower analyst coverage, higher analyst dispersion, and higher analyst forecast error. In Table A5, again using interaction tests, I show that the same level of innovation success leads to lower dividend payout ratios for firms facing higher information asymmetry.[42]

Second, I show that the impact of innovation success on financial policies of firms is stronger for younger firms compared to older firms. Given that younger firms face a greater extent of information asymmetry in the equity market compared to older firms, I expect that the impact of innovation success on information asymmetry and financial policies to be stronger for younger firms. In Table A6, using interaction tests, I show that the same level of innovation success reduces the information asymmetry faced by younger firms in the equity market to a greater extent than older firms. Next, in Table A7, using interaction tests, I show that the same level of innovation success leads to lower leverage ratios for younger firms compared to older firms. Again, since the extent of information asymmetry is greater for younger firms compared to older firms, a particular level of innovation success should have greater impact on leverage ratios of younger firms. Lastly, I show in Table A8, using interaction tests, that the same level of innovation success leads to lower dividend payout ratios for younger firms compared to older firms. Similar to the arguments given above, a particular level of innovation success should have greater impact on dividend payout ratios of younger firms (the extent of information asymmetry is greater for younger firms). These results supports my hypothesis that innovation success affects the financial policies of firms through the

[41] This is because the importance of quantity and quality of patents as signals of firms' research quality is greater for firms that face a greater degree of information asymmetry.

[42] I discuss these results in greater details in Section A4 of the appendix.

information asymmetry channel.

1.11 Ruling out Alternative Channels

In this section, I discuss some alternative channels through which innovation success may potentially affect the financial policies of firms, and rule out these channels using additional empirical tests.

1.11.1 Agency Cost-based Explanations

It may be argued that agency cost-based theories may also explain the impact of innovation success on the financial policies of firms. For example, Jensen and Meckling (1976) argue that there may be conflicts between equityholders and debtholders, since in a levered firm equityholders may have incentive to invest in value-reducing risky projects, i.e., "risk-shifting". Debtholders may anticipate this behavior of equityholders and factor this into the cost of debt, causing equityholders to bear this risk-shifting cost. In my setting, it is possible that creditors may believe that innovative firms have greater availability of riskier projects and are more likely to involve in risk-shifting activities. Creditors may also believe that firms pursuing riskier innovation strategies will involve more in risk-shifting activities. If this were the case, I would expect firms with higher innovation success to have lower leverage ratios and to have a greater propensity to issue equity rather than debt. I would also expect that, within a sample of innovative firms, firms pursuing riskier innovation strategies will have a greater propensity to issue equity rather than debt.

In another example of the agency cost of debt, Myers (1977) argues that debt-financing may give incentives to equityholders to underinvest in positive NPV projects that may primarily benefit debtholders rather than equityholders ("debt-overhang"). Based on the underinvestment incentive, Myers (1977) predicts that firms with greater growth opportunities will have lower leverage ratios. In my setting, it is possible that innovative firms have greater growth opportunities. Further, creditors may also assign a higher cost of debt to innovative firms, believing that such firms are risky. Innovating firms issuing risky debt may end up underinvesting to a greater extent in positive NPV projects, since they may face higher costs of debt. Thus, innovative firms may prefer to issue equity rather than debt to mitigate the above agency cost of debt, and will have lower leverage ratios. At the same time, firms pursuing riskier innovation strategy may face higher costs of debt and may have a greater extent of underinvestment. Thus, this particular agency cost-based explanation also suggests that, within a sample of innovative firms, firms pursuing riskier innovation strategies will have a greater propensity to issue equity rather than debt.

I now provide evidence that goes against the above agency cost-based explanations. I test these hypotheses analyzing the relationship between the riskiness of firms' innovation strategies and the external financing decisions of firms. In Table A-9 of the appendix, I show that, within a sample of innovative firms, the riskiness of a firm's innovation strategy is inconsequential to the firm's decision to issue equity rather than debt to raise external finance. In Table A-9, I show that the coefficients of the interaction of the riskiness of a firm's innovation strategy and its number of patents are insignificant.[43] In other words, within a sample of innovative firms, the riskiness of their innovation strategies is uncorrelated to their decision to issue equity rather than debt. Thus, I show that it is a firm's innovation success that affects its external financing; at the same time, the riskiness of its innovation strategy is irrelevant to its external financing. In summary, the evidence presented in Table A-9, rules out agency cost-based explanations.

1.11.2 Bankruptcy Cost-based Explanation

Innovation success may affect the leverage ratios of firms by affecting their bankruptcy costs. Innovation success may lead to higher future cash flows for a firm. Higher future cash flows, in turn, are likely to reduce the probability of default for the firm. Since the expected bankruptcy cost depends on the deadweight costs associated with bankruptcy and the probability of default, the expected bankruptcy cost will be lower if the probability of default goes down. Assuming that the tax benefits of debt are the same (or greater) for firms with higher innovation success, I would expect firms with higher innovation success to have higher leverage ratios through the above channel (since such firms will have lower expected bankruptcy costs). In summary, the bankruptcy cost-based arguments cannot explain my empirical results, since my results show that firms with higher innovation success have lower leverage ratios.

[43] I use the percentage of "explorative patents" and the percentage of "exploitative patents" of firms as the two measures of the riskiness of innovation strategy, following Custodio, Ferreira, and Matos (2017). An explorative patent is pushing a firm's knowledge in a new direction, where it has no prior experience, and is radical and risky. On the other hand, an exploitative patent is pushing a firm's knowledge in a direction, where it has significant prior experience, and is significantly less risky compared to an explorative patent. Please refer to Subsection A5 and Table A-9 in the appendix for more details.

1.12 Conclusion

In this paper, I investigate the impact of firms' innovation success on their financial policies. I hypothesize that, in a setting with information asymmetry between firm insiders and outside investors, innovation success may enable firms to credibly signal their intrinsic value to outside investors. This, in turn, will reduce the extent of information asymmetry faced by firms (with higher innovation success) in the equity market. Given this, such firms will have cheaper access to the equity market and consequently, will have lower leverage ratios. Using similar arguments, I expect that firms with higher innovation success will have a greater propensity to issue equity rather than debt to raise external finance. Additionally, these firms will need to rely less on dividends to signal their intrinsic value and consequently, will have lower dividend payout ratios. I test my predictions by analyzing a sample of U.S. public firms, using patent-based measures to capture innovation success. Specifically, for each firm, I use the log measure of its stock of patents and the log measure of the stock of citations per patent as proxies for innovation success.

Consistent with my hypotheses, I document that firms with higher innovation success have greater analyst coverage, lower analyst standard deviation, and lower analyst forecast error, i.e., they face lower information asymmetry. I also show that such firms have lower leverage ratios. Additionally, such firms have a greater propensity to issue equity rather than debt to raise external finance. Finally, I show that firms with higher innovation success have lower dividend payout ratios. All of my results are economically significant. To establish causality, I use the random assignment of patent applications to patent application examiners within an art-unit. I instrument the number of patents eventually granted to a firm by the average leniency of patent examiners assigned to a firm's patent applications. My IV analyses establish that all of my results are causal. My results are robust to using different measures of innovation success. I also provide cross-sectional evidence that supports the information asymmetry channel. Finally, I provide empirical evidence to rule out alternative explanations like agency cost and bankruptcy cost-based explanations.

References

Allen, Franklin, and Roni Michaely, 2003, Payout policy, in *Handbook of the Economics of Finance*, volume 1, 337–429 (Elsevier).

Asquith, Paul, and David W Mullins, 1983, The impact of initiating dividend payments on shareholders' wealth, *Journal of Business* 56.

Bae, Kee-Hong, René M Stulz, and Hongping Tan, 2008, Do local analysts know more? a cross-country study of the performance of local analysts and foreign analysts, *Journal of Financial Economics* 88, 581–606.

Behn, Bruce K., JongHag Choi, and Tony Kang, 2008, Audit Quality and Properties of Analyst Earnings Forecasts, *The Accounting Review* 83, 327–349.

Bernheim, B. Douglas, and Adam Wantz, 1995, A tax-based test of the dividend signaling hypothesis, *American Economic Review* 85, 532–551.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend, 2016, The Impact of Venture Capital Monitoring, *Journal of Finance* 71, 1591–1622.

Bloom, Nicholas, and John Van Reenen, 2002, Patents, real options and firm performance, *The Economic Journal* 112, C97–C116.

Bradley, Michael, Gregg A Jarrell, and E Kim, 1984, On the Existence of an Optimal Capital Structure: Theory and Evidence, *Journal of Finance* 39, 857–878.

Brown, James R, Steven M Fazzari, and Bruce C Petersen, 2009, Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom, *Journal of Finance* 64, 151–185.

Chang, Xin, Sudipto Dasgupta, and Gilles Hilary, 2006, Analyst Coverage and Financing Decisions, *Journal of Finance* 61, 3009–3048.

Chemmanur, Thomas J., Lei Kong, Karthik Krishnan, and Qianqian Yu, 2019, Top management human capital, inventor mobility, and corporate innovation, *Journal of Financial and Quantitative Analysis* 54, 23832422.

Chemmanur, Thomas J, Elena Loutskina, and Xuan Tian, 2014, Corporate venture capital, value creation, and innovation, *Review of Financial Studies* 27, 2434–2473.

Chemmanur, Thomas J, Imants Paeglis, and Karen Simonyan, 2009, Management quality, financial and investment policies, and asymmetric information, *Journal of Financial and Quantitative Analysis* 44, 1045–1079.

Chemmanur, Thomas J, and Xuan Tian, 2018, Do antitakeover provisions spur corporate innovation? A regression discontinuity analysis, *Journal of Financial and Quantitative Analysis* 53, 1163–1194.

Christie, Andrew A., 1987, On cross-sectional analysis in accounting research, *Journal of Accounting and Economics* 9, 231 – 258.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing innovation, *Review of Financial Studies* 26, 635–666.

Custódio, Cláudia, Miguel A Ferreira, and Pedro Matos, 2017, Do general managerial skills spur innovation?, *Management Science* 65, 459–476.

Dass, Nishant, Vikram K Nanda, and Steven Chong Xiao, 2015, Intellectual property protection and financial markets: Patenting vs. secrecy, *Working Paper* .

Easley, David, Nicholas M Kiefer, and Maureen O'Hara, 1997, One day in the life of a very common stock, *Review of Financial Studies* 10, 805–835.

Ederer, Florian, and Gustavo Manso, 2013, Is pay for performance detrimental to innovation?, *Management Science* 59, 1496–1513.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist, 2019, What is a patent worth? Evidence from the US patent "lottery", *Journal of Finance, Forthcoming* .

Floyd, Eric, Nan Li, and Douglas J Skinner, 2015, Payout policy through the financial crisis: The growth of repurchases and the resilience of dividends, *Journal of Financial Economics* 118, 299–316.

Gaule, Patrick, 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, John R, and Mark T Leary, 2011, A review of empirical capital structure research and directions for the future, *Annu. Rev. Financ. Econ.* 3, 309–345.

Graham, Stuart JH, Alan C Marco, and Richard Miller, 2015, The USPTO patent examination research dataset: A window on the process of patent examination, Working paper, Georgia Institute of Technology.

Hall, Bronwyn H, Adam Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working paper, National Bureau of Economic Research.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg, 2005, Market Value and Patent Citations, *The RAND Journal of Economics* 36, 16–38.

Harris, Milton, and Artur Raviv, 1991, The theory of capital structure, *Journal of Finance* 46, 297–355.

He, Jie, and Xuan Tian, 2018, Finance and corporate innovation: A survey, *Asia-Pacific Journal of Financial Studies* 47, 165–212.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative efficiency and stock returns, *Journal of Financial Economics* 107, 632–654.

Hovakimian, Armen, Tim Opler, and Sheridan Titman, 2001, The Debt-Equity Choice, *Journal of Financial and Quantitative Analysis* 36, 124.

Hsu, Po-Hsuan, Xuan Tian, and Yan Xu, 2014, Financial development and innovation: Cross-country evidence, *Journal of Financial Economics* 112, 116 – 135.

Jensen, Michael C., and William H. Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 3, 305 – 360.

John, Kose, and Joseph Williams, 1985, Dividends, Dilution, and Taxes: A Signalling Equilibrium, *Journal of Finance* 40, 1053–1070.

Kisgen, Darren J, 2006, Credit ratings and capital structure, *Journal of Finance* 61, 1035–1072.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *Quarterly Journal of Economics* 132, 665–712.

Korajczyk, Robert A, Deborah J Lucas, and Robert L McDonald, 1991, The effect of information releases on the pricing and timing of equity issues, *Review of Financial Studies* 4, 685–708.

Krishnaswami, Sudha, and Venkat Subramaniam, 1999, Information asymmetry, valuation, and the corporate spin-off decision, *Journal of Financial Economics* 53, 73 – 112.

Lemley, Mark A, 2000, Rational ignorance at the patent office, *Nw. UL Rev.* 95, 1495.

Lemley, Mark A, and Bhaven Sampat, 2012, Examiner characteristics and patent office outcomes, *Review of Economics and Statistics* 94, 817–827.

Lerner, Josh, and Amit Seru, 2017, The use and misuse of patent data: Issues for corporate finance and beyond, Working paper, National Bureau of Economic Research.

Li, Guan-Cheng, Ronald Lai, Alexander DAmour, David M Doolin, Ye Sun, Vetle I Torvik, Z Yu Amy, and Lee Fleming, 2014, Disambiguation and co-authorship networks of the us patent inventor database (1975–2010), *Research Policy* 43, 941–955.

Lin, Chen, Sibo Liu, and Gustavo Manso, 2016, Shareholder litigation and corporate innovation, *University of Hong Kong and University of California at Berkeley Working Paper* .

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand, 2013, Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt, *American Economic Review* 103, 1797–1829.

Mann, William, 2018, Creditor rights and innovation: Evidence from patent collateral, *Journal of Financial Economics* 130, 25–47.

Miller, Merton H., and Franco Modigliani, 1961, Dividend Policy, Growth, and the Valuation of Shares, *The Journal of Business* 34, 411–433.

Miller, Merton H, and Kevin Rock, 1985, Dividend Policy under Asymmetric Information, *Journal of Finance* 40, 1031–1051.

Modigliani, Franco, and Merton H. Miller, 1958, The Cost of Capital, Corporation Finance and the Theory of Investment, *American Economic Review* 48, 261–297.

Myers, Stewart C., 1977, Determinants of corporate borrowing, *Journal of Financial Economics* 5, 147 – 175.

Myers, Stewart C., and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187 – 221.

Nissim, Doron, and Amir Ziv, 2001, Dividend changes and future profitability, *Journal of Finance* 56, 2111–2133.

Rajan, Raghuram G, and Luigi Zingales, 1995, What Do We Know about Capital Structure? Some Evidence from International Data, *Journal of Finance* 50, 1421–1460.

Righi, Cesare, and Timothy Simcoe, 2019, Patent examiner specialization, *Research Policy* 48, 137–148.

Sampat, Bhaven, and Heidi L Williams, 2019, How do patents affect follow-on innovation? Evidence from the human genome, *American Economic Review* 109, 203–36.

Seru, Amit, 2014, Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics* 111, 381–405.

Shyam-Sunder, Lakshmi, and Stewart C Myers, 1999, Testing static tradeoff against pecking order models of capital structure, *Journal of Financial Economics* 51, 219 – 244.

Stock, James H., and Motohiro Yogo, 2002, Testing for Weak Instruments in Linear IV Regression, Working Paper 284, National Bureau of Economic Research.

Tian, Xuan, and Tracy Yue Wang, 2011, Tolerance for failure and corporate innovation, *Review of Financial Studies* 27, 211–255.

Titman, Sheridan, 1984, The effect of capital structure on a firm's liquidation decision, *Journal of Financial Economics* 13, 137–151.

Titman, Sheridan, and Roberto Wessels, 1988, The determinants of capital structure choice, *Journal of Finance* 43, 1–19.

Table 1: Summary Statistics

This table reports summary statistics for the sample of Compustat public firms in the U.S. between 1981 and 2013. Panel A reports summary statistics of independent and dependent variables for all Compustat firms in the sample period. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Total Assets)* is the natural logarithm of the book value of total assets of a firm. *Market to Book* is the ratio of market value of assets and the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Ln(1 + Stock of Citations/Patent)* is the natural logarithm of one plus the stock of total class-adjusted forward citations over the stock of total class-adjusted patents granted to the firm. *Book Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the book value of total assets. *Market Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the market value of total assets. The market value of assets is equal to the book value of assets minus the book value of equity plus the product of number of shares outstanding and share price. *Dividends/Income* is the dividend payout ratio, defined as the ratio of sum of common and preferred dividends over earnings before depreciation, interest, and taxes. *Ln(1+#Analysts)* is the number of analysts following a firm at the end of a fiscal year. *Analyst Dispersion* is the standard deviation of analyst forecasts scaled by the price per share at the end of a fiscal year. *Forecast Error* is the mean-squared error in the earnings forecast. I measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the price per share the end of a fiscal year. All dependent variables and all independent variables are winsorised at 1% and 99%. Panel B shows some characteristics of patent applications and patent examiners. The sample period is 2001 to 2014. I only include firm-year observations with at least one patent application in a rolling three-year period. *No. of Patent Applications* is the number of patent applications filed by a firm in a rolling three-year period. *No. of Patents* is the number of patent applications filed by a firm in a rolling three-year period, which are eventually granted. *Average Adjusted Leniency* is the average art-unit adjusted examiner leniency for a firm, computed over a rolling three-year period as per equation (5). *Application Success Rate* is the percentage of applications filed by a firm in a rolling three-year period, which are eventually granted as patents. *Art-unit adjusted Examiner Leniency (Annual)* is the annual art-unit adjusted examiner leniency over all the patent applications filed between 2001 and 2014. I only include examiners who have reviewed at least 10 applications in a calendar year, and art-units which have at least two examiners. Panel C shows normalized innovation success measures obtained from KPSS (2017) dataset. The sample period is 1981 to 2010 as KPSS data is available till 2010. I only include firm-year observations with at least one patent granted to a given firm in a given year. *Ln(Dollar Value Patents/Assets)* is the natural logarithm of total dollar value of all patents granted to a firm in a year scaled by the book value of assets of the firm. The dollar value of a patent is computed as the firm's market-adjusted abnormal return over the three-day window around the date of a patent approval multiplied by the firm's market capitalization on the day prior to the approval. *Ln(Citation Weighted Patents/Assets)* is the natural logarithm of one plus cohort-adjusted forward citations to all patents granted to a firm in a year scaled by the book value of assets of the firm.

Panel A: Summary Statistics of Compustat Firms

Variable	N	Mean	S.D.	1st Quartile	Median	3rd Quartile
Profitability	184,331	-0.136	0.959	-0.046	0.093	0.164
Ln(Sales)	177,710	4.177	2.695	2.499	4.304	6.056
Ln(Total Assets)	186,122	4.169	2.552	2.442	4.17	5.918
Market to Book	157,836	3.488	8.738	1.08	1.496	2.512
Ln(Age)	186,118	2.235	0.96	1.609	2.303	2.944
Tangible Asset	185,690	0.281	0.241	0.087	0.211	0.412
R&D Expenditure	186,122	0.072	0.203	0	0	0.055
Ln(1+Stock of Patents)	186,122	0.485	0.985	0	0	0.494
Ln(1+Stock of Citations/Patents)	186,122	0.003	0.007	0	0	0.003
Book Leverage	151,638	0.228	0.217	0.027	0.186	0.361
Market Leverage	151,638	0.169	0.181	0.011	0.111	0.272
Dividend/Income	173,830	0.062	0.163	0	0	0.049
Ln(1+#Analysts)	186,122	0.821	1.1	0	0	1.609
Analyst Dispersion	45,998	0.068	0.88	0.002	0.005	0.014
Forecast Error	45,998	0.101	1.269	0.002	0.005	0.017

Panel B: Summary Statistics of Patent Applications, Examiners, and Outcomes

Variable	N	Mean	S.D.	1st Quartile	Median	3rd Quartile
No. of Patent Applications	28,974	51.01	303.07	2	5	18
No. of Patents	28,974	40.92	247.74	1	3	14
Average Adjusted Leniency	28,974	0.01	0.09	-0.03	0.01	0.05
Application Success Rate	28,974	0.72	0.34	0.5	0.86	1
Art-unit adjusted Examiner Leniency (Annual)	96,829	-0.02	0.17	-0.12	-0.01	0.08

Panel C: Summary Statistics of KPSS measures

Variable	N	Mean	S.D.	1st Quartile	Median	3rd Quartile
Ln(Dollar Value Patents/Assets)	31,526	1.82	2.76	-0.21	1.46	3.58
Ln(Citation Weighted Patents/Assets)	31,526	2.29	1.62	1.04	2.02	3.22

Table 2: The Relation between Firms' Innovation Success and Information Asymmetry Facing them in the Equity Market: Baseline Analysis

This table reports the OLS regression results of the effect of firms' innovation success on the extent of information asymmetry facing them in the equity market. For each firm in the sample, I retrieve analysts' earnings forecasts from I/B/E/S for each fiscal year available. *Ln(1+#Analysts)* is the number of analysts following a firm at the end of a fiscal year. *Analyst Dispersion* is the standard deviation of analyst forecasts scaled by the price per share at the end of a fiscal year. *Forecast Error* is the mean-squared error in the earnings forecast. I measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the price per share at the end of a fiscal year. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Ln(1 + Stock of Citations/Patent)* is the natural logarithm of one plus the stock of total class-adjusted forward citations over the stock of total class-adjusted patents granted to the firm. *Ln(Total Assets)* is the natural logarithm of the book value of total assets of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Market to Book* is the ratio of market value of assets and the book value of assets. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Ln(1+#Analysts)	Analyst Dispersion	Forecast Error	Ln(1+#Analysts)	Analyst Dispersion	Forecast Error
Ln(1+Stock of Patents)	0.128***	-0.015***	-0.024***			
	(0.007)	(0.005)	(0.006)			
Ln(1+Stock of Citations/Patents)				7.835***	-1.540***	-2.270***
				(0.769)	(0.522)	(0.705)
Ln(Total Assets)	0.372***	-0.008**	-0.010*	0.395***	-0.014***	-0.019***
	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.005)
Ln(Age)	-0.166***	-0.012*	-0.017*	-0.147***	-0.015**	-0.022**
	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.009)
Market to Book	0.021***	-0.011***	-0.014***	0.023***	-0.011***	-0.015***
	(0.000)	(0.004)	(0.006)	(0.000)	(0.004)	(0.006)
R&D Expenditure	0.255***	0.718***	0.829***	0.292***	0.694***	0.789***
	(0.019)	(0.145)	(0.182)	(0.020)	(0.143)	(0.178)
Observations	141,316	44,707	44,707	141,316	44,707	44,707
Adjusted R-squared	0.594	0.013	0.012	0.588	0.013	0.012
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: The Relation between Firms' Innovation Success and Information Asymmetry Facing them in the Equity Market: Instrumental Variable Analysis

This table reports the instrumental variable regression results of the effect of firms' innovation success on the extent of information asymmetry facing them in the equity market. For each firm in the sample, I retrieve analysts' earnings forecasts from I/B/E/S for each fiscal year available. *Ln(1+#Analysts)* is the number of analysts following a firm at the end of a fiscal year. *Analyst Dispersion* is the standard deviation of analyst forecasts scaled by the price per share at the end of a fiscal year. *Forecast Error* is the mean-squared error in the earnings forecast. I measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the price per share at the end of a fiscal year. *Examiner Leniency* is the art unit-adjusted examiners' leniency averaged over all patent applications filed by a firm in a rolling three-year period. *Ln(1+#Patents)* is the natural logarithm of one plus the total number of patents applied and eventually granted to a firm in a rolling three-year period. *Predicted Ln(1+#Patents)* is the predicted value of the natural logarithm of one plus the total number of patents obtained from the first stage regression. *Ln(Total Assets)* is the natural logarithm of the book value of total assets of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Market to Book* is the ratio of market value of assets and the book value of assets. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. *No. of Patent Applications* is the number of patent applications filed by a firm in a rolling three-year period. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. I show the Cragg-Donald Wald F statistic in the table. All standard errors are clustered at the calendar year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	First Stage	Second Stage	First Stage	Second Stage	Second Stage
Variables	Ln(1+#Patents)	Ln(1+#Analyst)	Ln(1+#Patents)	Analyst Dispersion	Forecast Error
Examiner Leniency	0.835***		0.882***		
	(0.082)		(0.179)		
Predicted Ln(1+#Patents)		0.057		-0.285*	-0.371*
		(0.055)		(0.160)	(0.198)
Ln(Total Assets)	0.331***	0.416***	0.459***	0.102	0.135
	(0.012)	(0.017)	(0.027)	(0.066)	(0.081)
Ln(Age)	-0.017	-0.243***	0.056**	0.010	0.005
	(0.014)	(0.008)	(0.020)	(0.020)	(0.026)
Market to Book	0.008***	0.007***	0.039**	-0.038**	-0.047**
	(0.001)	(0.001)	(0.014)	(0.013)	(0.016)
R&D Expenditure	0.534***	0.325***	2.487***	2.170**	2.693**
	(0.018)	(0.031)	(0.179)	(0.753)	(0.979)
No. of Patent Applications	0.002***	-0.000	0.001***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	24,771	24,771	13,818	13,818	13,818
F Statistic from 1st Stage	118.151		51.222		
Adjusted R-squared	0.485		0.529		
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 4: The Relation between Firms' Innovation Success and their Capital Structure: Baseline Analysis

This table reports the OLS regression results of the effect of firms' innovation success on their capital structure. *Book Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the book value of total assets. *Market Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the market value of total assets. The market value of assets is equal to the book value of assets minus the book value of equity plus the product of number of shares outstanding and share price. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Ln(1 + Stock of Citations/Patent)* is the natural logarithm of one plus the stock of total class-adjusted forward citations over the stock of total class-adjusted patents granted to the firm. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
Variables	Book Leverage	Book Leverage	Market Leverage	Market Leverage
Ln(1+Stock of Patents)	-0.010***		-0.016***	
	(0.002)		(0.001)	
Ln(1+Stock of Citations/Patents)		-0.841***		-1.085***
		(0.181)		(0.148)
Tangible Asset	0.239***	0.239***	0.189***	0.191***
	(0.008)	(0.008)	(0.007)	(0.007)
Market to Book	-0.004***	-0.004***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
Profitability	-0.075***	-0.074***	-0.056***	-0.054***
	(0.003)	(0.003)	(0.003)	(0.003)
Ln(Sales)	0.011***	0.009***	0.011***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Age)	-0.006***	-0.007***	0.004**	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Dividend Payer Dummy	-0.017***	-0.017***	-0.025***	-0.026***
	(0.003)	(0.003)	(0.002)	(0.002)
R&D Expenditure	-0.144***	-0.148***	-0.151***	-0.160***
	(0.010)	(0.010)	(0.006)	(0.007)
Observations	129,918	129,918	129,918	129,918
Adjusted R-squared	0.163	0.162	0.235	0.231
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 5: The Relation between Firms' Innovation Success and their Capital Structure: Instrumental Variable Analysis

This table reports the instrumental variable regression results of the effect of firms' innovation success on their capital structure. *Book Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the book value of total assets. *Market Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the market value of total assets. The market value of assets is equal to the book value of assets minus the book value of equity plus the product of number of shares outstanding and share price. *Examiner Leniency* is the art unit-adjusted examiners' leniency averaged over all patent applications filed by a firm in a rolling three-year period. *Ln(1+#Patents)* is the natural logarithm of one plus the total number of patents granted to a firm in a rolling three-year period. *Predicted Ln(1+#Patents)* is the predicted value of the natural logarithm of one plus the total number of patents obtained from the first stage regression. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. *No. of Patent Applications* is the number of patent applications filed by a firm in a rolling three-year period. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. I show the Cragg-Donald Wald F statistic in the table. All standard errors are clustered at the calendar year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)
	First Stage	Second Stage	Second Stage
Variables	Ln(1+#Patents)	Book Leverage	Market Leverage
Examiner Leniency	0.852***		
	(0.081)		
Predicted Ln(1+#Patents)		-0.125**	-0.002
		(0.055)	(0.010)
Tangible Asset	-0.371***	0.221***	0.195***
	(0.042)	(0.048)	(0.012)
Market to Book	0.005***	0.016***	-0.001***
	(0.001)	(0.003)	(0.000)
Profitability	0.018	-0.204***	-0.021***
	(0.018)	(0.043)	(0.002)
Ln(Sales)	0.274***	0.015	0.006*
	(0.010)	(0.014)	(0.003)
Ln(Age)	-0.022	0.065***	0.006**
	(0.016)	(0.008)	(0.002)
Dividend Payer Dummy	-0.051***	0.017	-0.008***
	(0.013)	(0.011)	(0.002)
R&D Expenditure	0.713***	0.308**	-0.046***
	(0.046)	(0.124)	(0.010)
No. of Patent Applications	0.002***	0.000*	-0.000
	(0.000)	(0.000)	(0.000)
Observations	23,661	23,661	23,661
F Statistic from 1st Stage	105.739		
Adjusted R-squared	0.448		
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 6: The Impact of Firms' Information Asymmetry on their Capital Structure: Direct Test

This table reports the OLS regression results of the effect of information asymmetry faced by firms on their capital structure. Panel A shows the impact of analyst coverage on capital structure. *Ln(1+#Analysts)* is the number of analysts following a firm at the end of a fiscal year. Panel B shows the impact of analyst dispersion and analyst forecast error on capital structure. *Analyst Dispersion* is the standard deviation of analyst forecasts scaled by the price per share at the end of a fiscal year. *Forecast Error* is the mean-squared error in the earnings forecast. *Book Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the book value of total assets. *Market Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the market value of total assets. The market value of assets is equal to the book value of assets minus the book value of equity plus the product of number of shares outstanding and share price. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Ln(1 + Stock of Citations/Patent)* is the natural logarithm of one plus the stock of total class-adjusted forward citations over the stock of total class-adjusted patents granted to the firm. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: The Impact of Analyst Coverage on Capital Structure of Firms				
	(1)	(2)	(3)	(4)
Variables	Book Leverage		Market Leverage	
Ln(1+Stock of Patents)	-0.005***		-0.010***	
	(0.002)		(0.001)	
Ln(1+Stock of Citations/Patents)		-0.577***		-0.747***
		(0.179)		(0.141)
Ln(1+#Analysts)	-0.026***	-0.027***	-0.032***	-0.034***
	(0.001)	(0.001)	(0.001)	(0.001)
Tangible Asset	0.241***	0.241***	0.192***	0.193***
	(0.008)	(0.008)	(0.007)	(0.007)
Market to Book	-0.003***	-0.003***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Profitability	-0.073***	-0.072***	-0.053***	-0.052***
	(0.003)	(0.003)	(0.002)	(0.002)
Ln(Sales)	0.019***	0.018***	0.021***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Age)	-0.009***	-0.010***	-0.001	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Dividend Payer Dummy	-0.018***	-0.019***	-0.027***	-0.028***
	(0.003)	(0.003)	(0.002)	(0.002)
R&D Expenditure	-0.126***	-0.127***	-0.129***	-0.132***
	(0.010)	(0.010)	(0.006)	(0.006)
Observations	129,918	129,918	129,918	129,918
Adjusted R-squared	0.171	0.171	0.254	0.253
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Book Leverage				Market Leverage			
Ln(1+Stock of Patents)	-0.005***		-0.005***		-0.008***		-0.008***	
	(0.002)		(0.002)		(0.001)		(0.001)	
Ln(1+Stock of Citations/Patents)		-0.445*		-0.443*		-0.528***		-0.527***
		(0.242)		(0.242)		(0.181)		(0.181)
Dispersion	0.006*	0.006*			0.005**	0.005**		
	(0.003)	(0.003)			(0.002)	(0.002)		
Forecast Error			0.006***	0.006***			0.005***	0.005***
			(0.002)	(0.002)			(0.002)	(0.002)
Tangible Asset	0.188***	0.188***	0.188***	0.188***	0.147***	0.148***	0.147***	0.148***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)
Market to Book	-0.008***	-0.009***	-0.008***	-0.009***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Profitability	-0.256***	-0.254***	-0.255***	-0.253***	-0.253***	-0.250***	-0.252***	-0.249***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Sales)	0.019***	0.017***	0.019***	0.017***	0.014***	0.012***	0.014***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Age)	-0.010***	-0.012***	-0.010***	-0.012***	-0.008***	-0.010***	-0.008***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Dividend Payer Dummy	0.004	0.004	0.004	0.004	-0.006*	-0.006*	-0.006*	-0.006*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
R&D Expenditure	-0.301***	-0.312***	-0.300***	-0.311***	-0.341***	-0.357***	-0.340***	-0.356***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.020)	(0.021)	(0.020)	(0.020)
Observations	41,066	41,066	41,066	41,066	41,066	41,066	41,066	41,066
Adjusted R-squared	0.270	0.270	0.270	0.270	0.336	0.334	0.336	0.334
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: The Relation between Firms' Innovation Success and their Equity versus Debt Issues (Probit Model): Baseline Analysis

This table reports the probit regression results of the effect of firms' innovation success on their decisions to issue debt versus equity to raise external finance. The dependent variable, *Equity vs Debt*, equals one if equity is issued in the fiscal year, and zero if debt is issued. Net equity issue is defined as the ratio of the sale of common and preferred equity minus the purchase of common and preferred equity in a given year scaled by the book value of assets at the beginning of the year. Net debt is defined as the ratio of the long-term debt issuance in a given year minus the long-term debt reduction in the year plus the change in current debt in a given year scaled by the book value of the assets at the beginning of the fiscal year. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by book value of assets exceeds 5%. Observations where firms issue both equity and debt in a given fiscal year are dropped. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Ln(1 + Stock of Citations/Patent)* is the natural logarithm of one plus the stock of total class-adjusted forward citations over the stock of total class-adjusted patents granted to the firm. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)
	Probit Model	
Variables	Equity vs Debt	Equity vs Debt
Ln(1+Stock of Patents)	0.043***	
	(0.006)	
Ln(1+Stock of Citations/Patents)		3.225***
		(0.696)
Tangible Asset	-0.189***	-0.188***
	(0.025)	(0.025)
Market to Book	0.001	0.001
	(0.001)	(0.001)
Profitability	0.067***	0.065***
	(0.008)	(0.008)
Ln(Sales)	-0.051***	-0.046***
	(0.002)	(0.002)
Ln(Age)	-0.092***	-0.087***
	(0.006)	(0.006)
Dividend Payer Dummy	-0.031***	-0.028***
	(0.010)	(0.010)
R&D Expenditure	0.298***	0.302***
	(0.030)	(0.031)
Observations	18,306	18,306
Pseudo R2	0.171	0.170
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 8: The Relation between Firms' Innovation Success and their Equity versus Debt Issues: Instrumental Variable Analysis

This table reports the instrumental variable analysis using the probit model to show the effect of firms' innovation success on their decisions to issue debt versus equity to raise external finance. The dependent variable, *Equity vs Debt*, equals one if equity is issued in the fiscal year, and zero if debt is issued. Net equity issue is defined as the ratio of the sale of common and preferred equity minus the purchase of common and preferred equity in a given year scaled by the book value of assets at the beginning of the year. Net debt is defined as the ratio of the long-term debt issuance in a given year minus the long-term debt reduction in the year plus the change in current debt in a given year scaled by the book value of the assets at the beginning of the fiscal year. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by book value of assets exceeds 5%. Observations where firms issue both equity and debt in a given fiscal year are dropped. *Examiner Leniency* is the art unit-adjusted examiners' leniency averaged over all patent applications filed by a firm in a rolling three-year period. *Ln(1+#Patents)* is the natural logarithm of one plus the total number of patents applied and eventually granted to a firm in a rolling three-year period. *Predicted Ln(1+#Patents)* is the predicted value of the natural logarithm of one plus the total number of patents obtained from the first stage regression. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. *No. of Patent Applications* is the number of patent applications filed by a firm in a rolling three-year period. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. I show the Cragg-Donald Wald F statistic in the table. All standard errors are clustered at the calendar year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	Probit Model	
	First Stage	Second Stage
Variables	Ln(1+#Patents)	Equity vs Debt
Examiner Leniency	1.008***	
	(0.185)	
Predicted Ln(1+#Patents)		0.255***
		(0.048)
Tangible Asset	-0.244	-0.226**
	(0.167)	(0.101)
Market to Book	0.004***	-0.003***
	(0.001)	(0.001)
Profitability	-0.017	0.026***
	(0.021)	(0.009)
Ln(Sales)	0.230***	-0.102***
	(0.012)	(0.008)
Ln(Age)	0.069*	-0.142***
	(0.038)	(0.021)
Dividend Payer Dummy	-0.040	-0.084***
	(0.041)	(0.027)
R&D Expenditure	0.168*	0.134***
	(0.084)	(0.050)
No. of Patent Applications	0.001***	-0.001***
	(0.000)	(0.000)
Observations	2,586	2,586
F Statistic from 1st Stage	58.439	
R-squared	0.466	
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 9: The Relation between Firms' Innovation Success and their Dividend Payout Ratios: Baseline Analysis

This table reports the OLS regression results of the effect of firms' innovation success on their dividend payout ratios. *Dividends/Income* is the dividend payout ratio, defined as the ratio of sum of common and preferred dividends over earnings before depreciation, interest, and taxes. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Ln(1 + Stock of Citations/Patent)* is the natural logarithm of one plus the stock of total class-adjusted forward citations over the stock of total class-adjusted patents granted to the firm. *Profitability* is defined as operating income before depreciation over the book value of assets. *Cash Flow Volatility* is defined as the standard deviation of a firm's profitability over the previous four years with at least two years of data during the prior four years. *Cash/Asset* is defined as the total cash and marketable securities of a firm scaled by the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Sales Growth* is defined as the difference between sales in the current year and the last year, scaled by the sales in the last year. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)
Variables	Dividend/Income	
Ln(1+Stock of Patents)	-0.0002	
	(0.001)	
Ln(1+Stock of Citations/Patents)		-0.334***
		(0.120)
Profitability	0.000	-0.000
	(0.001)	(0.001)
Cash Flow Volatility	0.002	0.002
	(0.001)	(0.001)
Cash/Asset	0.029***	0.030***
	(0.006)	(0.006)
Ln(Sales)	0.009***	0.009***
	(0.001)	(0.001)
Ln(Age)	0.026***	0.027***
	(0.002)	(0.002)
Sales Growth	-0.004***	-0.004***
	(0.000)	(0.000)
R&D Expenditure	-0.034***	-0.033***
	(0.005)	(0.005)
Observations	120,608	120,608
Adjusted R-squared	0.086	0.086
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 10: The Relation between Firms' Innovation Success and their Dividend Payout Ratios: Instrumental Variable Analysis

This table reports the instrumental variable regression results of the effect of firms' innovation success on their dividend payout ratios. *Dividends/Income* is the dividend payout ratio, defined as the ratio of sum of common and preferred dividends over earnings before depreciation, interest, and taxes. *Examiner Leniency* is the art unit-adjusted examiners' leniency averaged over all patent applications filed by a firm in a rolling three-year period. *Ln(1+#Patents)* is the natural logarithm of one plus the total number of patents applied and eventually granted to a firm in a rolling three-year period. *Predicted Ln(1+#Patents)* is the predicted value of the natural logarithm of one plus the total number of patents obtained from the first stage regression. *Profitability* is defined as operating income before depreciation over the book value of assets. *Cash Flow Volatility* is defined as the standard deviation of a firm's profitability over the previous four years with at least two years of data during the prior four years. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Cash/Asset* is defined as the total cash and marketable securities of a firm scaled by the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Sales Growth* is defined as the difference between sales in the current year and the last year, scaled by the sales in the last year. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. *No. of Patent Applications* is the number of patent applications filed by a firm in a rolling three-year period. Constant, three-digit SIC industry fixed effects, and year fixed effects are included in all regressions. I show the Cragg-Donald Wald F statistic in the table. All standard errors are clustered at the two-digit SIC industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)
	First Stage	Second Stage
Variables	Ln(1+#Patents)	Dividend/Income
Examiner Leniency	0.879***	
	(0.104)	
Predicted Ln(1+#Patents)		-0.055***
		(0.016)
Profitability	-0.031*	-0.001
	(0.017)	(0.001)
Cash Flow Volatility	0.073***	0.006***
	(0.015)	(0.001)
Ln(Sales)	0.330***	0.024***
	(0.011)	(0.005)
Cash/Asset	1.234***	0.078***
	(0.037)	(0.021)
Ln(Age)	0.047**	0.040***
	(0.016)	(0.002)
Sales Growth	-0.010	-0.004***
	(0.011)	(0.001)
R&D Expenditure	0.766***	0.008
	(0.052)	(0.014)
No. of Patent Applications	0.001***	0.000***
	(0.000)	(0.000)
Observations	19,254	19,254
F Statistic from 1st Stage	93.763	
Adjusted R-squared	0.469	
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 11: The Relation between normalized measures of Firms' Innovation Success and Information Asymmetry Facing them in the Equity Market: Robustness Tests

This table reports the OLS regression results of the effect of firms' innovation success on the extent of information asymmetry facing them in the equity market, using scaled measures of innovation success described below. *Ln(Dollar Value Patents/Assets)* is the natural logarithm of total dollar value of all patents granted to a firm in a year scaled by the book value of assets of the firm. The dollar value of a patent is computed as the firm's market-adjusted abnormal return over the three-day window around the date of a patent approval multiplied by the firm's market capitalization on the day prior to the approval. *Ln(Citation Weighted Patents/Assets)* is the natural logarithm of one plus cohort-adjusted forward citations to all patents granted to a firm in a year scaled by the book value of assets of the firm. Both these measures are obtained from KPSS (2017). *Ln(1+#Analysts)* is the number of analysts following a firm at the end of a fiscal year. *Analyst Dispersion* is the standard deviation of analyst forecasts scaled by the price per share at the end of a fiscal year. *Forecast Error* is the mean-squared error in the earnings forecast. I measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the price per share at the end of a fiscal year. *Ln(Total Assets)* is the natural logarithm of the book value of total assets of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Market to Book* is the ratio of market value of assets and the book value of assets. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Ln(1+#Analysts)	Analyst Dispersion	Forecast Error	Ln(1+#Analysts)	Analyst Dispersion	Forecast Error
Ln(Dollar Value Patents/Assets)	0.126***	-0.019**	-0.032**			
	(0.007)	(0.009)	(0.013)			
Ln(Citation Weighted Patents/Assets)				0.038***	-0.019**	-0.027**
				(0.007)	(0.008)	(0.011)
Ln(Total Assets)	0.315***	0.007	0.018	0.455***	-0.005	-0.005
	(0.010)	(0.010)	(0.015)	(0.007)	(0.004)	(0.006)
Ln(Age)	-0.238***	-0.003	-0.007	-0.254***	-0.002	-0.006
	(0.013)	(0.012)	(0.018)	(0.013)	(0.013)	(0.018)
Market to Book	0.053***	-0.020***	-0.024***	0.080***	-0.023***	-0.030***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.006)	(0.007)
R&D Expenditure	0.107**	0.915***	1.112***	0.314***	0.916***	1.098***
	(0.052)	(0.215)	(0.270)	(0.055)	(0.217)	(0.270)
Observations	29,735	16,112	16,112	29,735	16,112	16,112
Adjusted R-squared	0.635	0.012	0.010	0.622	0.012	0.010
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: The Relation between normalized measures of Firms' Innovation Success and their Capital Structure: Robustness Tests

This table reports the OLS regression results of the effect of innovation success of firms on their capital structure, using scaled measures of innovation success described below. *Ln(Dollar Value Patents/Assets)* is the natural logarithm of total dollar value of all patents granted to a firm in a year scaled by the book value of assets of the firm. The dollar value of a patent is computed as the firm's market-adjusted abnormal return over the three-day window around the date of a patent approval multiplied by the firm's market capitalization on the day prior to the approval. *Ln(Citation Weighted Patents/Assets)* is the natural logarithm of one plus cohort-adjusted forward citations to all patents granted to a firm in a year scaled by the book value of assets of the firm. Both these measures are obtained from KPSS (2017). *Book Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the book value of total assets. *Market Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the market value of total assets. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Variables	(1) Book Leverage	(2) Market Leverage	(3) Book Leverage	(4) Market Leverage
Ln(Dollar Value Patents/Assets)	-0.011***	-0.016***		
	(0.001)	(0.001)		
Ln(Citation Weighted Patents/Assets)			-0.009***	-0.011***
			(0.002)	(0.001)
Tangible Asset	0.163***	0.122***	0.168***	0.130***
	(0.017)	(0.013)	(0.017)	(0.014)
Market to Book	-0.004***	-0.009***	-0.006***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Profitability	-0.182***	-0.154***	-0.177***	-0.146***
	(0.012)	(0.008)	(0.011)	(0.008)
Ln(Sales)	0.027***	0.028***	0.019***	0.015***
	(0.002)	(0.001)	(0.001)	(0.001)
Ln(Age)	0.004	0.004	0.006*	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Dividend Payer Dummy	-0.020***	-0.023***	-0.020***	-0.023***
	(0.005)	(0.004)	(0.005)	(0.004)
R&D Expenditure	-0.189***	-0.181***	-0.200***	-0.198***
	(0.020)	(0.012)	(0.020)	(0.012)
Observations	28,998	28,998	28,998	28,998
Adjusted R-squared	0.173	0.298	0.168	0.280
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

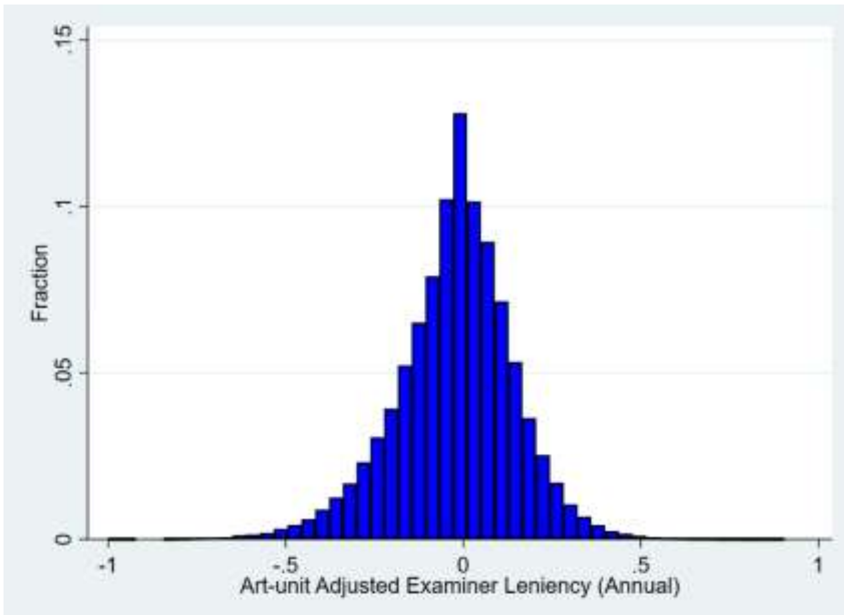
Table 13: The Relation between normalized measures of Firms' Innovation Success and their Equity versus Debt Issues (Probit Model): Robustness Tests

This table reports the probit model regression results of the effect of firms' innovation success on their decision to issue debt versus equity to raise external finance, using scaled measures of innovation success described below. *Ln(Dollar Value Patents/Assets)* is the natural logarithm of total dollar value of the patents granted to a firm in a year scaled by the book value of assets of the firm. The dollar value of a patent is computed as the firm's market-adjusted abnormal return over the three-day window around the date of a patent approval multiplied by the firm's market capitalization on the day prior to the approval. *Ln(Citation Weighted Patents/Assets)* is the natural logarithm of one plus cohort-adjusted forward citations to all patents granted to a firm in a year scaled by the book value of assets of the firm. Both these measures are obtained from KPSS (2017). The dependent variable, *Equity vs Debt*, equals one if equity is issued in the fiscal year, and zero if debt is issued. Net equity issue is defined as the ratio of the sale of common and preferred equity minus the purchase of common and preferred equity in a given year scaled by the book value of assets at the beginning of the year. Net debt is defined as the ratio of the long-term debt issuance in a given year minus the long-term debt reduction in the year plus the change in current debt in a given year scaled by the book value of the assets at the beginning of the fiscal year. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by book value of assets exceeds 5%. Observations where firms issue both equity and debt in a given fiscal year are dropped. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of the sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)
	Probit Model	
Variables	Equity vs Debt	
Ln(Dollar Value Patents/Assets)	0.033***	
	(0.008)	
Ln(Citation Weighted Patents/Assets)		0.034***
		(0.008)
Tangible Asset	-0.136	-0.145*
	(0.086)	(0.084)
Market to Book	0.039***	0.046***
	(0.007)	(0.007)
Profitability	-0.006	-0.013
	(0.060)	(0.061)
Ln(Sales)	-0.090***	-0.071***
	(0.012)	(0.008)
Ln(Age)	-0.059***	-0.062***
	(0.016)	(0.016)
Dividend Payer Dummy	-0.067***	-0.065**
	(0.025)	(0.025)
R&D Expenditure	0.434***	0.451***
	(0.117)	(0.119)
Observations	3,507	3,507
Pseudo R2	0.334	0.334
Industry FE	Yes	Yes
Year FE	Yes	Yes

Figure 1: Distribution of Patent Examiners' Approval Rates

This figure shows the sample distribution of patent examiners' approval rates adjusted to the overall approval rate of the respective art-units, defined by subtracting equation (4) from equation (3). The sample comprises all examiner-year leniency data computed using all the patent applications data available at the USPTO website from 2001 to 2014. I exclude examiners who have reviewed less than 10 applications in a given year.



Appendix

This appendix comprises five sections. In Section A1, I show that there is no correlation between the current average examiner leniency (over a set of patent applications) for a firm and the future number of patent applications filed by the firm. Next, I check the correlation between my instrument (average examiner leniency) and firm characteristics. In Section A2, I show that my instrument is uncorrelated to observable firm characteristics. In Section A3, I show that my results on the impact of innovation success on equity versus debt issues are robust to using linear probability models. Next, I provide additional evidence which supports my hypothesis that the impact of innovation success on financial policies of firms is driven by the information asymmetry channel. In Section A4, I conduct cross-sectional analyses across firms facing lower versus higher information asymmetry and across age groups of firms to provide additional evidence that innovation success affects the financial policies of firms through the information asymmetry channel. Lastly, in Section A5, I show that a firm's riskiness of its innovation strategy does not affect its decision to issue equity versus debt. As discussed in my main text, this test rules out the view that results are driven by agency cost-based explanations like "risk-shifting" or "debt overhang." I now discuss the above results in detail in the following sections.

A1. The Effect of Examiner leniency on Future Patent Applications filed by Firms

In Table A-1, I present the results of my OLS regression analysis of the relation between the examiner leniency on current set of patent applications of a firm and the future patent applications filed by the firm. One may be concerned about the use of average examiner leniency as an instrument, since it may have an impact on the future number of patent applications made by a firm. I address this concern by show that there is no correlation between the current average examiner leniency and the number of patent applications filed by a firm in the future. To run these tests, I compute the number of applications filed by firms in the future one-, two-, three-, four-, and five-year period and regress them on average examiner leniency, which I use as my IV. I control for firm characteristics like profitability, market to book, firm age, firm size, and R&D expenditure. I report these results in Table A-1. In Column (1), for any year t, *Ln(1+ Applications) (1 Year)* is the number of patent applications filed by a firm in the next year (year *t+1*). Similarly, in Column (2), *Ln(1+ Applications) (2 Years)* is the number of patent applications filed by a firm in the next two years (from year *t+1* to *t+2*). In Column (3), *Ln(1+ Applications) (3 Years)* is the number of patent applications filed by a firm in the next three years (from year *t+1* to *t+3*). In Column (4), *Ln(1+ Applications) (4 Years)* is the number of patent applications filed by a firm in the next four years (from year *t+1* to *t+4*). In Column (5), *Ln(1+ Applications) (5 Years)* is the number of patent applications filed by a firm in the next five years (from year *t+1* to *t+5*).

I show that the average examiner leniency is not correlated with the number of future patent applications filed by a firm. These results are robust to using different time windows to measure the number of future applications. Additionally, as I show in the next section, average examiner leniency is uncorrelated with firm characteristics.

A2. Average Examiner Leniency is uncorrelated with Firm Characteristics

In Table A-2, I test the correlation between the examiner leniency and firm characteristics. I regress *average examiner leniency*, my IV, on firm characteristics like profitability, market to book, firm age, firm size, and R&D expenditure. I show that my IV is uncorrelated with these firm characteristics. I include industry and year fixed effects and cluster standard error at calendar year level, exactly as in my IV analyses shown in the main part of my paper. In Column (1), I regress average examiner leniency on the number of patent applications filed by the firm and show that they are uncorrelated. In column (2), I regress average examiner leniency on profitability, market to book, firm age, firm size, and R&D expenditure and show that none of these firm characteristics are correlated to average examiner leniency. Lastly, in Column (3), I regress average examiner leniency on all the above variables and show that examiner leniency is uncorrelated to these variables. Thus, my results provide evidence that examiner leniency is unaffected by firm characteristics.

A3. The Effect of Firms' Innovation Success on their Equity versus Debt Issues (using a Linear Probability Model): OLS and IV Analysis

In the main text of my paper, I show that firms with higher innovation success have a greater propensity to issue equity rather than debt using baseline probit model and probit model with IV. In Table A-3, I provide support for the above results using a linear probability model and conducting both OLS and IV analyses. I have the same set of controls, fixed effects, and cluster standard errors in the same manner as in the main part of my paper. Panel A shows the results of OLS analyses. I provide evidence that firms with a higher quantity and quality of innovation success (as captured by the stock of patents and stock of citations per patent) have a greater propensity to issue equity rather than debt. My results are significant at the 1% level. Panel B shows the results of corresponding IV analyses. The first stage Cragg-Donald Wald F statistic is 58.439. The coefficient of estimated patent measure is significant at the 5% level. My IV analysis result is in the same direction as my OLS analysis, and supports my hypothesis **H3**.

A4. The Effect of Firms' Innovation Success on their Financial Policies: Cross-Sectional Analysis

In this section, I provide additional evidence that innovation success affects the financial policies of firms through the information asymmetry channel. I conduct cross-sectional analyses across firms facing lower versus higher information asymmetry and separately, across age groups of firms. I discuss my cross-sectional results in the following subsections.

A4.1 The Effect of Firms' Innovation Success on their Capital Structure: Cross-Sectional Analysis across Low and High Information Asymmetry Groups

In Table A4, I show that the same level of innovation success leads to lower leverage ratios for firms facing higher information asymmetry, i.e., firms having lower analyst coverage, higher analyst dispersion, and higher analyst forecast error. I segment firms into two groups of above the median (higher) information asymmetry and below the median (lower) information asymmetry. The coefficient of interaction of analyst coverage and stock of patents is positive. This implies that the same level of innovation success leads to lower leverage ratios for firms with lower analyst coverage (higher information asymmetry). Similarly, the coefficients of interaction of analyst dispersion and stock of patents, and analyst forecast error and stock of patents are negative. This implies that the same level of innovation success leads to lower leverage ratios for firms with higher analyst dispersion and higher analyst forecast error. These results show that the impact of innovation success on leverage ratios is stronger for firms facing higher information asymmetry in the equity market, which supports the information asymmetry channel. I also show that analyst coverage is negatively correlated (significant at 1% level) with leverage ratios. Further, I show that analyst dispersion and analyst forecast error are positively correlated (significant at 1% levels) with leverage ratios. This implies that firms facing lower information asymmetry have lower leverage ratios. Thus, this test provides direct evidence that firms facing lower information asymmetry have lower leverage ratios.

A4.2 The Effect of Firms' Innovation Success on their Dividend Payout Ratios: Cross-Sectional Analysis across Low and High Information Asymmetry Groups

In Table A5, I show that the same level of innovation success leads to lower dividend payout ratios for firms facing higher information asymmetry, i.e., firms having lower analyst coverage, higher analyst dispersion, and higher analyst forecast error. The coefficient of interaction of analyst coverage and stock of patents is positive, but insignificant. Similarly, the coefficients of interaction of analyst dispersion and stock of patents, and analyst forecast error and stock of patents are negative (significant at 1% levels). This implies that the same level of innovation success leads to lower dividend payout ratios for firms with higher analyst dispersion and higher analyst forecast error. These results show that the impact of innovation success on dividend payout ratios is stronger for firms facing higher information asymmetry in the equity market, which supports the information asymmetry channel. I show that analyst coverage is negatively correlated (significant at 1% level) with leverage ratios. I also show that analyst dispersion and analyst forecast error are positively correlated (significant at 1% levels) with leverage ratios. This implies that firms facing lower information asymmetry have lower dividend payout ratios. Thus, this test also provides direct evidence that firms facing lower information asymmetry have lower dividend payout ratios.

A4.3 The Effect of Firms' Innovation Success on the Extent of Information Asymmetry Facing them in the Equity Market: Cross-Sectional Analysis across Firm-Age Groups

I conduct OLS analysis to show that the effect of innovation success on information asymmetry faced by firms in the equity market is greater for younger firms. Following Brown, Fazzari, and Petersen (2009), I classify a firm as *Younger Firms* for the first 15 years following the year the firm first appears in Compustat database, after 15 years firms are classified as *Older Firms.* Table A-6 shows the cross sectional results using OLS analyses. My dependent variables are analyst dispersion and analyst forecast error. In Column (1) and Column (2), the coefficients of the interaction of the log measure of the stock of patents and firm-age indicator are negative and significant at 1% and 10% levels, respectively. These result show that innovation success reduces the extent of information asymmetry faced by younger public firms to a greater extent than older public firms, thereby supporting the information asymmetry channel.

A4.4 The Effect of Firms' Innovation Success on their Capital Structure: Cross-Sectional Analysis across Firm-Age Groups

I conduct OLS analysis to show that the effect of innovation success on capital structure of firms is greater for younger firms. Table A-7 shows the cross sectional results using OLS analyses. I use the log measure of the stock of patents as my main independent variable and use the same set of controls and fixed effects as in my baseline analyses in the main paper. I use book and market leverage as measures of capital structure. In Column (1) and Column (2), the coefficients of the interaction of the log measure of the stock of patents and firm-age indicator are negative and significant at 1% level. Thus, innovation success leads to lower book leverage for younger firms, which are the ones most affected by information asymmetry.

A4.5 The Effect of Firms' Innovation Success on their Dividend Payout Ratios: Cross-Sectional Analysis across Firm-Age Groups

I conduct OLS analysis to show that the effect of innovation success on dividend payout ratios of firms is greater for younger firms. Table A-8 shows the cross sectional results using OLS analyses. I use the log measure of the stock of patents as my main independent variable and use the same set of controls and fixed effects as in my baseline analyses in the main paper. I show that firms with higher stock of patents have lower dividend payout ratios. In Column (1), the coefficient of the interaction of the log measure of the stock of patents and firm-age indicator is negative and significant at 1% level. These results show that innovation success is associated with lower dividend payout ratios for younger firms compared to older firms.

A5. The Effect of the Riskiness of Firms' Innovation Strategies on their Equity versus Debt Issues

I show that, within a sample of innovative firms, the riskiness of firms' innovation strategies are irrelevant to their decision to issue equity versus debt to raise external finance. As I discuss in the main text of my paper, this result goes against the agency cost-based explanations. Following Custodio, Ferreira, and Matos (2017), I classify a firm's patents into "explorative" and "exploitative." Explorative patents, which are based on the new knowledge of a firm, are risky or radical innovation by the firm. Exploitative patents, in contrast, are the patents, which are based on the existing knowledge of the firm. Existing knowledge includes a firm's previous patent portfolio and all patents that were cited by the firm's patents filed over the past 5 years. New knowledge includes all patents except for a firm's previous patent portfolio and all patents that were cited by the firm's patents filed over the past 5 years. A patent is exploitative if at least 60% of its citations refer to existing knowledge; a patent is explorative if at least 60% of its citations refer to new knowledge. Following Custodio, Ferreira, and Matos (2017), I define a firm's innovation strategy by computing the percentage of explorative or exploitative patents a firm was granted in one year out of the total number of patents granted in the year.

I estimate the following linear probability model:

$$Pr[Issue{=}1]_{i,t+1} = \alpha_0 + \alpha_1 Innov_{i,t} + X_{i,t} + \alpha_2 Innov_{i,t} \times Strategy_{i,t} + \alpha_3 Strategy_{i,t} + X_{i,t} + \epsilon_{i,t+1}, \tag{1}$$

where i indexes firm and t index time. *Issue* is a dummy variable which takes the value one if the firm issues equity in the year and zero if the firm issues debt. $Innov_{i,t}$ represents the number of patents granted to the firm in a year.[1] $Strategy_{i,t}$ represents either the percentage of explorative or exploitative patents a firm is granted in a year. $X_{i,t}$ represents the vector of controls used in my baseline specifications. All independent variables are lagged by one year. I have industry and year fixed effects in my specification. My sample consists of firm-year observations with at least one patent in a given year. In Table A-9, I show that the coefficients of the interaction of innovation strategy measures and the number of patents of a firm are insignificant. This implies

[1]Results are robust to using the economic value of patents following KPSS (2017)

that, within a sample of innovative firms, the riskiness of their innovation strategies are irrelevant for their external financing decisions. Thus, it is a firm's innovation success which affects its external financing, but the riskiness of its innovation strategy is irrelevant to its external financing decisions. As I discussed in my main paper, these result go against agency cost-based explanations on the impact of innovation success on financial policies of firms.

References

Brown, James R, Steven M Fazzari, and Bruce C Petersen, 2009, Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom, *The Journal of Finance* 64, 151–185.

Custódio, Cláudia, Miguel A Ferreira, and Pedro Matos, 2017, Do general managerial skills spur innovation?, *Management Science* 65, 459–476.

Table A-1

The Effect of Examiner leniency on Future Patent Applications filed by Firms

This table reports the OLS regression results of regressing the number of future patent applications filed by a firm on the average examiner leniency based on current set of patent applications filed by the firm. In any year *t*, *Ln(1+ # Applications) (1 Year)* is the natural logarithm of one plus the number of patent applications filed by a firm in the next year (year t+1). *Ln(1+ # Applications) (2 Years)* is the natural logarithm of one plus the number of patent applications filed by a firm in the next two years (from year t+1 to t+2). *Ln(1+ # Applications) (3 Years)* is the natural logarithm of one plus the number of patent applications filed by a firm in the next three years (from year t+1 to t+3). *Ln(1+ # Applications) (4 Years)* is the natural logarithm of one plus the number of patent applications filed by a firm in the next four years (from year t+1 to t+4). *Ln(1+ # Applications) (5 Years)* is the natural logarithm of one plus the number of patent applications filed by a firm in the next five years (from year t+1 to t+5). The sample period is from 2001 to 2014, which is same as my instrumental variable analyses. *Average Examiner Leniency* in any year *t* is the art unit-adjusted examiners' leniency averaged over all the patent applications filed by a firm in the prior three-year period (from t-2 to t). *Profitability* is defined as operating income before depreciation over the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. I include calendar year and two-digit SIC industry fixed effects in all specifications. All standard errors are clustered at the calendar year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Ln (1 + #Applications)				
Variables	(1 Year)	(2 Years)	(3 Years)	(4 Years)	(5 Years)
Average Examiner Leniency	-0.112	-0.195	-0.227	-0.197	-0.222
	(0.105)	(0.116)	(0.141)	(0.172)	(0.217)
Profitability	0.016	0.032	0.050*	0.073*	0.109**
	(0.018)	(0.024)	(0.028)	(0.035)	(0.046)
Market to Book	0.007***	0.008***	0.010***	0.013***	0.015***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Ln(Sales)	0.266***	0.318***	0.349***	0.372***	0.388***
	(0.021)	(0.018)	(0.016)	(0.016)	(0.017)
Ln(Age)	-0.032**	-0.060***	-0.076***	-0.083***	-0.092***
	(0.011)	(0.010)	(0.010)	(0.013)	(0.013)
R&D Expenditure	0.675***	0.898***	1.051***	1.186***	1.336***
	(0.060)	(0.059)	(0.077)	(0.093)	(0.122)
Observations	25,075	22,193	19,462	16,993	14,769
Adjusted R-squared	0.302	0.307	0.307	0.312	0.318
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table A-2

Regression Analysis showing that Firm Characteristics are uncorrelated with Average Examiner Leniency

This table reports the OLS regression results of regressing examiner leniency on firm characteristics. *Average Examiner Leniency* is the art unit-adjusted examiners' leniency averaged over all patent applications filed by a firm in a rolling three-year period. *No. of Patent Applications* is the number of patent applications filed by a firm in a rolling three-year period. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the calendar year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)
Variables	Average Examiner Leniency		
No. of Patent Applications	0.0000		-0.0000
	(0.0000)		(0.0000)
Market to Book		-0.0001	-0.0001
		(0.0001)	(0.0001)
Profitability		0.0017	0.0017
		(0.0013)	(0.0013)
Ln(Sales)		0.0007	0.0007
		(0.0005)	(0.0005)
Ln(Age)		0.0005	0.0005
		(0.0009)	(0.0009)
R&D Expenditure		0.0008	0.0009
		(0.0036)	(0.0036)
Observations	28,974	25,511	25,511
Adjusted R-squared	0.0116	0.0146	0.0145
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table A-3

The Relation between Firms' Innovation Success and their Equity versus Debt Issues (Linear Probability Model): OLS and Instrumental Variable Analysis

This table reports the OLS and instrumental variable regression results of the effect of firms' innovation success on their decisions to issue debt versus equity, using a linear probability model. The dependent variable, *Equity vs Debt*, equals one if equity is issued in the fiscal year, and zero if debt is issued. Net equity issue is defined as the ratio of the sale of common and preferred equity minus the purchase of common and preferred equity in a given year scaled by the book value of assets at the beginning of the year. Net debt is defined as the ratio of the long-term debt issuance in a given year minus the long-term debt reduction in the year plus the change in current debt in a given year scaled by the book value of the assets at the beginning of the fiscal year. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by book value of assets exceeds 5%. Observations where firms issue both equity and debt in a given fiscal year are dropped. Panel A shows the results of OLS regressions. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Ln(1 + Stock of Citations/Patent)* is the natural logarithm of one plus the stock of total class-adjusted forward citations over the stock of total class-adjusted patents granted to the firm. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively. Panel B shows the results of instrumental variable regressions. *Examiner Leniency* is the art unit-adjusted examiners' leniency averaged over all patent applications filed by a firm in a rolling three-year period. *Ln(1+#Patents)* is the natural logarithm of one plus the total number of patents applied and eventually granted to a firm in a rolling three-year period. *Predicted Ln(1+#Patents)* is the predicted value of natural logarithm of one plus the total number of patents obtained from the first stage regression. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. *No. of Patent Applications* is the number of patent applications filed by a firm in a rolling three-year period. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. I show the Cragg-Donald Wald F statistic in the table. All standard errors are clustered at the calendar year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: OLS Analysis of the impact of Innovation Success on Equity vs Debt issue		
	(1)	(2)
	Linear Probability Model	
Variables	Equity vs Debt	Equity vs Debt
Ln(1+Stock of Patents)	0.038***	
	(0.004)	
Ln(1+Stock of Citations/Patents)		2.944***
		(0.607)
Tangible Asset	-0.173***	-0.174***
	(0.022)	(0.022)
Market to Book	0.001	0.001
	(0.001)	(0.001)
Profitability	0.062***	0.060***
	(0.007)	(0.007)
Ln(Sales)	-0.045***	-0.040***
	(0.002)	(0.002)
Ln(Age)	-0.076***	-0.071***
	(0.005)	(0.005)
Dividend Payer Dummy	-0.017*	-0.013
	(0.009)	(0.009)
R&D Expenditure	0.282***	0.285***
	(0.025)	(0.025)
Observations	18,311	18,311
Adjusted R-squared	0.201	0.199
Industry FE	Yes	Yes
Year FE	Yes	Yes

Panel B: Instrumental Variable Analysis of the impact of Innovation Success on Equity vs Debt Issue		
	Linear Probability Model	
	First Stage	Second Stage
Variables	Ln(1+#Patents)	Equity vs Debt
Examiner Leniency	1.008***	
	(0.185)	
Predicted Ln(1+#Patents)		0.201**
		(0.091)
Tangible Asset	-0.244	-0.230**
	(0.167)	(0.077)
Market to Book	0.004***	-0.003***
	(0.001)	(0.001)
Profitability	-0.017	0.025**
	(0.021)	(0.009)
Ln(Sales)	0.230***	-0.090***
	(0.012)	(0.023)
Ln(Age)	0.069*	-0.128***
	(0.038)	(0.014)
Dividend Payer Dummy	-0.040	-0.064***
	(0.041)	(0.015)
R&D Expenditure	0.168*	0.139***
	(0.084)	(0.037)
No. of Patent Applications	0.001***	-0.000**
	(0.000)	(0.000)
Observations	2,641	2,641
F Statistic from 1st Stage	58.439	
R-squared	0.466	
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table A-4

The Relation between Firms' Innovation Success and their Capital Structure: Cross-Sectional Analysis across Low and High Information Asymmetry Groups

This table reports the cross-sectional OLS regression results of the effect of firms' innovation success on their capital structure. *Book Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the book value of total assets. *Market Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the market value of total assets. The market value of assets is equal to the book value of assets minus the book value of equity plus the product of number of shares outstanding and share price. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Analyst Coverage* is an indicator variable that takes the value 0 if not a single analyst follow a firm; otherwise, it takes the value 1. *Analyst Forecast Error* is an indicator variable that takes the value 0 in a given year if a firm is below median in terms of analyst forecast error across all firms in the year; otherwise, it takes the value 1. *Dispersion* is an indicator variable that takes the value 0 in a given year if a firm is below median in terms of analyst dispersion across all firms in that year; otherwise, it takes the value 1. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		Book Leverage			Market Leverage	
Ln(1+Stock of Patents)	-0.026***	-0.003	-0.002	-0.023***	-0.005***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Analyst Coverage	-0.057***			-0.049***		
	(0.003)			(0.003)		
Ln(1+Stock of Patents) x Analyst Coverage	0.020***			0.009***		
	(0.002)			(0.002)		
Analyst Forecast Error		0.045***			0.060***	
		(0.004)			(0.003)	
Ln(1+Stock of Patents) x Analyst Forecast Error		-0.005**			-0.005***	
		(0.002)			(0.002)	
Dispersion			0.046***			0.061***
			(0.004)			(0.003)
Ln(1+Stock of Patents) x Dispersion			-0.006**			-0.006***
			(0.002)			(0.002)
Tangible Asset	0.239***	0.180***	0.179***	0.190***	0.136***	0.135***
	(0.008)	(0.015)	(0.015)	(0.007)	(0.012)	(0.012)
Market to Book	-0.003***	-0.006***	-0.006***	-0.007***	-0.011***	-0.011***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Profitability	-0.072***	-0.223***	-0.223***	-0.053***	-0.205***	-0.205***
	(0.003)	(0.015)	(0.015)	(0.002)	(0.011)	(0.011)
Ln(Sales)	0.017***	0.020***	0.020***	0.017***	0.016***	0.016***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Ln(Age)	-0.009***	-0.010***	-0.010***	0.000	-0.007***	-0.007***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Dividend Payer Dummy	-0.018***	0.006	0.006	-0.026***	-0.003	-0.003
	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)
R&D Expenditure	-0.121***	-0.298***	-0.300***	-0.132***	-0.338***	-0.341***
	(0.010)	(0.028)	(0.028)	(0.006)	(0.019)	(0.019)
Observations	129,918	41,066	41,066	129,918	41,066	41,066
Adjusted R-squared	0.172	0.278	0.278	0.245	0.359	0.359
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A-5

The Relation between Firms' Innovation Success and their Dividend Payout Ratios: Cross-Sectional Analysis across Low and High Information Asymmetry Groups

This table reports the cross-sectional OLS regression results of the effect of firms' innovation success on their dividend payout ratios. *Dividends/Income* is the dividend payout ratio, defined as the ratio of sum of common and preferred dividends over earnings before depreciation, interest, and taxes. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Analyst Coverage* is an indicator variable that takes the value 0 if not a single analyst follow a firm; otherwise, it takes the value 1. *Analyst Forecast Error* is an indicator variable that takes the value 0 in a given year if a firm is below median in terms of analyst forecast error across all firms in the year; otherwise, it takes the value 1. *Dispersion* is an indicator variable that takes the value 0 in a given year if a firm is below median in terms of analyst dispersion across all firms in that year; otherwise, it takes the value 1. *Profitability* is defined as operating income before depreciation over the book value of assets. *Cash Flow Volatility* is defined as the standard deviation of a firm's *profitability* over the previous four years with at least two years of data during the prior four years. *Cash/Asset* is defined as the total cash and marketable securities of a firm scaled by the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Sales Growth* is defined as the difference between sales in the current year and the last year, scaled by the sales in the last year. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)
Variables		Dividend Payout Ratio	
Ln(1+Stock of Patents)	0.000	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
Analyst Coverage	-0.017***		
	(0.003)		
Ln(1+Stock of Patents) x Analyst Coverage	0.000		
	(0.002)		
Analyst Forecast Error		0.009***	
		(0.003)	
Ln(1+Stock of Patents) x Analyst Forecast Error		-0.007***	
		(0.001)	
Dispersion			0.008***
			(0.003)
Ln(1+Stock of Patents) x Dispersion			-0.007***
			(0.001)
Profitability	0.000	0.016	0.015
	(0.001)	(0.010)	(0.010)
Cash Flow Volatility	0.001	0.001	0.001
	(0.001)	(0.005)	(0.005)
Cash/Asset	0.036***	0.016*	0.016*
	(0.006)	(0.009)	(0.009)
Ln(Sales)	0.011***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)
Ln(Age)	0.025***	0.025***	0.025***
	(0.002)	(0.002)	(0.002)
Sales Growth	-0.004***	-0.006***	-0.006***
	(0.000)	(0.001)	(0.001)
R&D Expenditure	-0.031***	-0.114***	-0.114***
	(0.004)	(0.014)	(0.014)
Observations	120,608	40,245	40,245
Adjusted R-squared	0.087	0.172	0.172
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table A-6

The Relation between Firms' Innovation Success and Information Asymmetry Facing them in the Equity Market: Cross-Sectional Analysis across Firm-Age Groups

This table reports the cross-sectional OLS regression results of the effect of firms' innovation success on the extent of information asymmetry facing them in the equity market. For each firm in the sample, I retrieve analysts' earnings forecasts from I/B/E/S for each fiscal year available. *Analyst Dispersion* is the standard deviation of analyst forecasts scaled by the price per share at the end of a fiscal year. *Forecast Error* is the mean-squared error in the earnings forecast. I measure forecast error as the absolute difference between the average forecasted earnings and the actual earnings per share divided by the price per share at the end of a fiscal year. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Young Firm* is an indicator variable, which takes the value 1 for the first 15 years following the year a firm first appears in Compustat database, otherwise the indicator variable takes the value 0. *Ln(Total Assets)* is the natural logarithm of the book value of total assets of a firm. *Market to Book* is the ratio of market value of assets and the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)
Variables	Analyst Dispersion	Forecast Error
Ln(1+Stock of Patents)	-0.010***	-0.019***
	(0.004)	(0.006)
Young Firm	-0.013	-0.009
	(0.018)	(0.027)
Ln(1+Stock of Patents) x Young Firm	-0.017***	-0.019*
	(0.006)	(0.010)
Ln(Total Assets)	-0.009**	-0.011*
	(0.004)	(0.006)
Market to Book	-0.011***	-0.015***
	(0.004)	(0.006)
Ln(Age)	-0.025**	-0.029*
	(0.011)	(0.015)
R&D Expenditure	0.738***	0.850***
	(0.148)	(0.185)
Observations	44,707	44,707
Adjusted R-squared	0.013	0.012
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table A-7

The Relation between Firms' Innovation Success and their Capital Structure: Cross-Sectional Analysis across Firm-Age Groups

This table reports the cross-sectional OLS regression results of the effect of firms' innovation success on their capital structure. *Book Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the book value of total assets. *Market Leverage* is defined as the book value of long-term debt plus debt in current liabilities divided by the market value of total assets. The market value of assets is equal to the book value of assets minus the book value of equity plus the product of number of shares outstanding and share price. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Young Firm* is an indicator variable, which takes the value 1 for the first 15 years following the year a firm first appears in Compustat database, otherwise the indicator variable takes the value 0. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Variables	(1) Book Leverage	(2) Market Leverage
Ln(1+Stock of Patents)	-0.006***	-0.014***
	(0.002)	(0.001)
Young Firm	0.031***	0.026***
	(0.004)	(0.003)
Ln(1+Stock of Patents) x Young Firm	-0.014***	-0.008***
	(0.003)	(0.002)
Tangible Asset	0.238***	0.189***
	(0.008)	(0.007)
Market to Book	-0.003***	-0.007***
	(0.000)	(0.000)
Profitability	-0.074***	-0.055***
	(0.003)	(0.003)
Ln(Sales)	0.011***	0.011***
	(0.001)	(0.001)
Ln(Age)	0.005**	0.013***
	(0.002)	(0.002)
Dividend Payer Dummy	-0.016***	-0.025***
	(0.003)	(0.002)
R&D Expenditure	-0.141***	-0.151***
	(0.010)	(0.006)
Observations	129,918	129,918
Adjusted R-squared	0.165	0.237
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table A-8

The Relation between Firms' Innovation Success and their Dividend Payout Ratios: Cross-Sectional Analysis across Firm-Age Groups

This table reports the cross-sectional OLS regression results of the effect of firms' innovation success on their dividend payout ratios. *Dividends/Income* is the dividend payout ratio, defined as the ratio of sum of common and preferred dividends over earnings before depreciation, interest, and taxes. *Ln(1 + Stock of Patents)* is the natural logarithm of one plus the stock of class-adjusted patents granted to a firm. *Young Firm* is an indicator variable, which takes the value 1 for the first 15 years following the year a firm first appears in Compustat database, otherwise the indicator variable takes the value 0. *Profitability* is defined as operating income before depreciation over the book value of assets. *Cash Flow Volatility* is defined as the standard deviation of a firm's *profitability* over the previous four years with at least two years of data during the prior four years. *Cash/Asset* is defined as the total cash and marketable securities of a firm scaled by the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Sales Growth* is defined as the difference between sales in the current year and the last year, scaled by the sales in the last year. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Variables	(1) Dividend/Income
Ln(1+Stock of Patents)	0.004***
	(0.001)
Young Firm	-0.003
	(0.003)
Ln(1+Stock of Patents) x Young Firm	-0.014***
	(0.002)
Profitability	0.001
	(0.001)
Cash Flow Volatility	0.001
	(0.001)
Cash/Asset	0.032***
	(0.006)
Ln(Sales)	0.009***
	(0.001)
Ln(Age)	0.021***
	(0.002)
Sales Growth	-0.004***
	(0.000)
R&D Expenditure	-0.030***
	(0.004)
Observations	120,608
Adjusted R-squared	0.088
Industry FE	Yes
Year FE	Yes

Table A-9

The Relation between Firms' Innovation Success and their Equity versus Debt Issues: Cross-Sectional Analysis across the Riskiness of Innovation Strategies

This table reports the cross-sectional OLS regression results of the effect of firms' innovation success on their decisions to issue debt versus equity, using a linear probability model. The dependent variable, *Equity vs Debt*, equals one if equity is issued in the fiscal year, and zero if debt is issued. Net equity issue is defined as the ratio of the sale of common and preferred equity minus the purchase of common and preferred equity in a given year scaled by the book value of assets at the beginning of the year. Net debt is defined as the ratio of the long-term debt issuance in a given year minus the long-term debt reduction in the year plus the change in current debt in a given year scaled by the book value of the assets at the beginning of the fiscal year. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by book value of assets exceeds 5%. Observations where firms issue both equity and debt in a given fiscal year are dropped. *Ln(1 + # Patents)* is the natural logarithm of one plus the number of patents granted to a firm in a year. *% Exploitative Patents* is the percentage of all the patents granted to a firm in a year, which are exploitative. *% Explorative Patents* is the percentage of all the patents granted to a firm in a year, which are explorative. A patent is exploitative if at least 60% of its citations refer to existing knowledge; a patent is explorative if at least 60% of its citations refer to new knowledge. Existing knowledge includes a firm's previous patent portfolio and all the patents that were cited by the firm's patents filed over the past 5 years. New knowledge include any patent except a firm's previous patent portfolio and all the patents that were cited by the firm's patents filed over the past 5 years. *Tangible asset* is the book value of property, plant, and equipment divided by the book value of assets. *Market to Book* is the ratio of market value of assets and the book value of assets. *Profitability* is defined as operating income before depreciation over the book value of assets. *Ln(Sales)* is the natural logarithm of sales turnover of a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has data available from Compustat database. *Dividend Payer Dummy* is an indicator variable equal to 1 if a firm pays dividend in a year and zero otherwise. *R&D Expenditure* is the ratio of R&D expenditure of a firm and the book value of total assets. Constant (suppressed in the tables), two-digit SIC industry fixed effects, and year fixed effects are included in all regressions. All standard errors are clustered at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Variables	(1)	(2) Equity vs Debt	(3)
Ln(1 +#Patents)	0.025***	0.024**	0.022*
	(0.007)	(0.010)	(0.013)
Ln(1+#Patents) x % Exploitative Patents		-0.000	
		(0.000)	
% Exploitative Patents		0.000	
		(0.000)	
Ln(1+#Patents) x % Explorative Patents			0.000
			(0.000)
% Exploratory Patents			-0.000
			(0.000)
Tangible Asset	-0.221***	-0.221***	-0.222***
	(0.053)	(0.053)	(0.053)
Market to Book	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)
Profitability	0.082***	0.081***	0.080***
	(0.030)	(0.030)	(0.030)
Ln(Sales)	-0.055***	-0.054***	-0.055***
	(0.005)	(0.005)	(0.005)
Ln(Age)	-0.070***	-0.070***	-0.071***
	(0.012)	(0.012)	(0.012)
Dividend Payer Dummy	-0.055***	-0.055***	-0.054***
	(0.018)	(0.018)	(0.018)
R&D Expenditure	0.333***	0.333***	0.332***
	(0.055)	(0.054)	(0.055)
Observations	4,075	4,075	4,075
Adjusted R-squared	0.345	0.345	0.345
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Chapter 2

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

2.1 Introduction

Trademarks are an important determinant of the economic value created by firms.[1] A trademark is a word, symbol, or other signifier used to distinguish a good or service produced by one firm from the goods or services of other firms (see, e.g., Landes and Posner (1987)). Firms use trademarks to differentiate their products from those of other firms, reduce search costs for consumers, and to generate consumer loyalty through advertising, all of which may affect their product market performance and therefore their financial performance. However, despite the importance of trademarks for the economic activities of firms, there is a relatively little evidence on the role played by trademarks in entrepreneurial finance: i.e., in the financing, performance, and valuation of young firms at various stages in their life.[2]

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

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

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

post-IPO operating performance of the subsample of these firms that go public.

We hypothesize that trademarks play two economically important roles in entrepreneurial finance. First, as we discussed earlier, trademarks allow start-up firms to differentiate their products from those of other firms, reduce search costs for consumers, and to generate consumer loyalty through advertising, all of which may affect their product market performance and therefore their financial performance. From now onwards we will refer to this role of trademarks as a "protective role." Second, trademarks may convey credible (but possibly noisy) information about future firm performance (and therefore intrinsic firm value) to private investors such as VCs and public equity market investors, in a setting of asymmetric information between firm insiders and outside investors. Different from patents (which primarily capture technological innovation), a trademark may signal the intention and ability of a firm to launch and continue a new product line (associated with that trademark). Therefore, assuming that it is costly to acquire and maintain trademarks, a firm's trademark portfolio may serve as a credible signal of firm value to both private investors and public equity market investors (such as investors in the IPO market or potential acquirers of the firm).[3] From now onwards, we will refer to this role of trademarks as their "informational role."

The above broad hypotheses about the protective and the informational role of trademarks generate two sets of testable predictions about entrepreneurial firms. The first set of testable predictions deal with private firms. First, given that firms with a larger number of trademarks are likely to have better future financial performance and this information is inferred by private equity investors (such as VCs) by observing the number of trademarks registered by these firms, we would expect, *ceteris paribus*, the amount of VC investment in private firms to be positively related to the number of trademarks held by these firms.[4] Second, one of the reasons for staging suggested by the

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

[4]It is well-known among practitioners (such as entrepreneurs and VCs) that intellectual property is an important determinant of VC investment in a private firm: see, e.g., the news article, "Do Venture Capitalists Care about Intellectual Property?", *Forbes Magazine*, August 11, 2015. However, the focus in the academic literature has only

literature on VC staging is to take advantage of the real option to discontinue further investment in a firm as they accumulate more information about the firm over time. Since trademarks may convey information to VCs about future firm performance (and therefore about intrinsic firm value), this motivation of VC staging suggests that the number of stages of VC investment will be negatively related to the number of trademarks registered by the firm. Third, we expect private firms with a larger number of trademarks to have a greater probability of a successful exit either through an IPO or an acquisition. This may arise partially due to the protective role of trademarks (which enable firms with a larger number of trademarks to have better future financial performance) and partially due to the informational role of trademarks (since a larger number of trademarks may convey information about better future firm performance to both potential IPO market investors and to potential acquirers).

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

been on the relation between the size of the patent portfolio of a start-up firm and the signal it sends to investors: see, e.g, Hsu and Ziedonis (2008).

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

We now discuss the results of our empirical analysis. We first summarize the results of our first set of empirical tests, which analyze the impact of the number of trademarks held by private firms on the investment behavior of VCs in these firms and on the exit decisions of these firms. First, private firms with a larger number of trademarks are associated with a larger amount of total VC investment. This result is statistically and economically significant. A one standard deviation increase in our trademark measure is associated with a 1.1 percent (0.27 million dollars) increase in total funding for the median firm in our sample. Second, private firms with a larger number of trademarks are associated with a lower extent of staging by VCs. A one standard deviation increase in our trademark measure is associated with a 3.2 percent increase in the fraction of investment in round 1 for the median firm. Consistent with this, the total number of rounds of VC investment also declines with the number of trademarks held by the firm at the time of initial VC investment. Lastly, private firms with a larger number of trademarks have a greater chance of a successful exit. A one standard deviation increase in our trademark measure is associated with a 3.1 percentage point increase in the probability of successful exit, where successful exit is defined as exit either through an IPO or an acquisition. Overall, the results of our first set of empirical tests provide support for both the protective and the informational role of trademarks. It is also important to note that, in all our empirical tests, we control for the number of patents held by a firm and the number of citations to these patents.[5]

We now summarize the results of our second set of empirical tests which analyze the relation between the number of trademarks held by a firm at the time of IPO and its IPO characteristics and post-IPO operating performance. First, VC-backed firms with a larger number of trademarks have higher IPO and immediate secondary market valuations. A one standard deviation increase in our trademark measure is associated with 8 percent and 7.3 percent average increase in IPO and immediate secondary market valuations, respectively (as measured by their Tobin's Q). Second, VC-backed firms going public with a larger number of trademarks are associated with greater institutional investor participation at the IPO. A one standard deviation increase in our trademark measure is associated with a 0.2 percent average increase in the number of institutional investors investing in firms. Third, VC-backed firms going public with a larger number of trademarks at IPO are associated with better post-IPO operating performance. In terms of economic magnitude, a one standard deviation increase in our trademark measure is associated with an increase of 0.051 in *OIBDA* (the ratio of operating income before depreciation plus interest income to the book value of total assets). This increase is substantial, given that the median value of *OIBDA* in the first year after IPO is -0.15. Fourth, such firms face a smaller extent of information asymmetry in the equity market, as measured by analyst coverage and dispersion in analyst forecasts. A one standard deviation increase in our trademark measure is associated with a 21.1 percent decrease in the mean dispersion in analyst forecasts and a 6 percent increase in the average analyst coverage. Overall, the results of our second set of empirical tests provide further support for the protective and informational roles of trademarks. In particular, the results of our empirical analysis of the post-IPO operating performance of the subset of VC-backed firms going public provide direct support for the protective role of trademarks, while the results of our empirical analysis of the post-IPO information asymmetry facing such firms provide direct support for the informational role of trademarks.

It may be argued that the relations we have established so far using our baseline analysis between

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

a larger number of trademarks and various private firm and IPO characteristics are endogenous. For example, a higher quality private firm may apply and receive a larger number of trademarks, so that the relations that we documented above between the number of trademarks and the probability of successful private firm exit may be the result of higher firm quality rather than the number of trademarks held by the firm. We, therefore, use an instrumental variable (IV) analysis to establish causality.[6] We instrument for the number of trademarks registered by a firm using a measure of trademark examiner leniency. Trademark applications are randomly assigned to examining attorneys (examiners), who have significant discretion in the examining process. This exogenous variation in examiner leniency may affect the outcome of applications which are on the margin of acceptance or rejection. We, therefore, instrument for the number of granted trademarks using the average examiner leniency calculated across all the trademark applications (accepted or rejected) made by a firm in a two-year period. The results of our IV analysis establish that VC-backed firms with a larger number of trademarks have a greater chance of a successful exit. Further, we show that firms with a larger number of trademarks have higher IPO and immediate secondary market valuations, have greater institutional investor participation, have better post-IPO operating performance, and face a smaller extent of information asymmetry in the post-IPO equity market.

The rest of the paper is organized as follows. Section 2 discusses the relation of our paper to the existing literature. Section 3 outlines the underlying theory and develops testable hypotheses for our empirical tests. Section 4 describes institutional details of the trademark application process and associated costs. Section 5 describes our data and sample selection procedures. Section 6 presents our empirical analyses and results. Section 7 concludes. The results of our propensity-score matching analyses are presented in an appendix.

2.2 Relation to the Existing Literature and Contribution

Our paper is related to several strands in the literature. One strand in the literature related to our paper is the one that analyses how intellectual property (such as patents and trademarks)

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

held by private firms affects the investment decisions of VCs in these firms and firm valuation by VCs, as well as their valuation at IPO and their post-IPO operating performance. Block, De Vries, Schumman, and Sandner (2014) show that the number and breadth of trademarks have inverted U-shaped relation with financial valuation of start-ups by VCs.[7] Our paper is also related to papers analyzing the relation between the patents held by private firms at IPO, their IPO valuation, and their post-IPO performance: see, e.g., Chemmanur, Gupta, and Simonyan (2016), who study the relation between private firms' innovation at IPO and their IPO and secondary market valuation, and their post-IPO operating performance; and Cao, Jiang, and Ritter (2013), who study the relation between the number of patents held by VC-backed firms at IPO and their post-IPO stock returns.

In contrast to the above literature, ours is the first paper to analyze the relation between the number of trademarks held by private firms and VC investment patterns (total investment and staging of investment) and the relation between the number of trademarks held by private firms and their probability of successful exit. It is also the first to analyze the relation between the number of trademarks and the IPO characteristics of VC-backed private firms going public (IPO and immediate secondary market valuations, institutional investor participation in the IPO, post-IPO information asymmetry), and also the first to analyze the relation between the number of trademarks held by a private firm at IPO and its post-IPO operating performance. Finally, it is also the first paper to demonstrate a causal relation between the number of trademarks held by a private firm and the above mentioned variables.[8]

Our paper also contributes to several strands in the broader entrepreneurial finance and the IPO literature. First, we contribute to the literature dealing with investment behavior of VCs in private firms: see, e.g., Gompers (1995), who analyzes how agency costs and information asymmetry affect VC staging, and Tian (2011), who studies how the distance between VC investors and start-up firms affect the staging of VC investments. Second, we contribute to the literature dealing with

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

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

the exit decisions of private firms: see, e.g., Lerner (1994), who analyzes the going public decisions of venture-backed private firms; Chemmanur, He, and Nandy (2009), who analyze the relation between the product market characteristics of private firms and their going public decisions; and Chemmanur, He, He, and Nandy (2018), who analyze the relation between the product market characteristics of private firms and their exit choice between IPOs, acquisitions, and remaining private. Third, we contribute to the literature relating various characteristics of a private firm at IPO and its IPO characteristics: see, e.g., Chemmanur and Paeglis (2005), who analyze the relation between the top management quality of a firm at IPO and its IPO characteristics.[9] Fourth, we contribute to the literature relating various characteristics of private firms to their IPO and post-IPO operating performance: see, e.g., Jain and Kini (1994) and Loughran and Ritter (1997). Our paper contributes indirectly to this strand in the literature by showing, for the first time, that an important determinant of private firm success is the portfolio of trademarks held by them.

Finally, our paper is also related to the literature on the role of trademarks, patents, and other forms of intellectual property in established (seasoned) firms.[10] Faurel, Li, Shanthikumar, and Teoh (2016) use a sample of publicly traded (S&P 1500) firms to analyze the relation between CEO incentives and the number of trademarks created by firms. Hsu, Li, Liu, and Wu (2017) demonstrate that companies with large portfolios of trademarks and fast growth in trademarks are likely to be acquirers, while companies with a narrow breadth of trademarks and slow growth in trademarks are likely to be target firms. Exploiting the Federal Trademark Dilution Act (FTDA), Heath and Mace (2019) find that stronger trademark protection has negative effect on innovation and product quality. Unlike the above papers that focus on the role of trademarks in established firms, the focus of our paper is on how trademarks help the performance of private firms and firms going public.

2.3 Theory and Hypotheses Development

We hypothesize that trademarks play two economically important roles relevant for the financing of private firms and their exit decisions. First, they may help to distinguish the products of a

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

[10] For an excellent review of the economics of intellectual property, see Besen and Raskind (1991).

firm from those sold by other firms: see, e.g., Economides (1988).[11] In other words, trademarks give the owner legal protection by granting the exclusive right to use them to identify goods or services, or to license its use to another entity in return for payment (see, e.g., Mendonça, Pereira, and Godinho (2004)). Further, trademarks may help to enhance the product market performance of the firms which own trademarks in a variety of other ways. For example, in a setting where sellers have better information about the unobservable features of the product than consumers themselves, trademarks accomplish two tasks (see, Economides (1988)): (i) They facilitate and enhance consumer decisions by identifying the unobservable features of the trademarked product; (ii) they create incentives for firms to produce products of desirable quality even when quality is not observable before purchase. They may also allow for "perception advertising" whereby a mental image may be added to the quality and various other features of a trademarked product. This allows the firm to generate consumer loyalty to trademarks, thus deterring entry by competitors. In summary, trademarks may enhance the value of the firm's products (and its product market performance) in many different ways. This, in turn, implies that trademarks may also help to enhance the future financial performance of a firm. We refer to this direct effect of trademarks on the future financial performance of a private firm as the "protective" role of trademarks.[12]

The second important economic role that trademarks may play in the life of young firms is of conveying information about their intrinsic value and future financial performance to investors. In other words, they may act as a credible (but possibly noisy) signal to private investors such as VCs and public equity market investors, in a setting of asymmetric information between firm insiders and outside investors. Different from patents (which primarily capture technological innovation), a trademark may signal the intention and ability of a firm to launch and continue a new product line (associated with that trademark).[13] Therefore, assuming that it is costly to acquire and maintain

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

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

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

trademarks, a firm's trademark portfolio may serve as a credible signal of intrinsic firm value to both private investors and public equity market investors (such as investors in the IPO market or potential acquirers of the firm), over and above any information conveyed by the firm's patent portfolio.[14] We will refer to this role of trademarks as their "informational" role.[15]

Of course, the number of trademarks registered by a firm may not be a fully revealing signal of firm value. In other words, if the cost of acquiring a trademark is not higher than the valuation and other benefits obtained by the firm from registering it, the equilibrium in the financial market (either in the private or in the public equity market) may be a partial pooling equilibrium (rather than a fully separating equilibrium). Thus, firms having a wide range of intrinsic values may pool together partially by acquiring the same number of trademarks (i.e., within a certain band of characteristics, higher intrinsic valued firms may be unable to fully distinguish themselves credibly from lower intrinsic valued firms using only their trademarks). Nevertheless, even in the case of a partial pooling equilibrium, investors may be able obtain some information, albeit noisy, about the future performance of a firm from observing the number of trademarks registered by it.[16]

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

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

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

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

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

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

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

The Relation between Trademarks and Venture Capital Staging

We now turn to the relation between the number of trademarks registered by a firm and the extent of staging of VC investment (i.e, the number of rounds the total VC investment in the firm is split up into). It has been argued that VC staging and monitoring are substitutes (see, e.g., Tian (2011)). This is because, given that investing in a larger number of rounds is associated with greater contracting and other costs, VCs are likely to invest in higher quality firms (requiring less monitoring) using a smaller number of stages (investment rounds). Given that a larger number of trademarks registered to a firm may signal higher firm quality (higher intrinsic value and better future operating performance), this means that the number of stages of VC investment will be negatively related to the number of trademarks registered by a firm.[17] Given the smaller number of financing rounds that a VC's total investment is split up into, we also expect firms holding a larger number of trademarks to be associated with a larger fraction of the total VC investment to

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

be made in the firm in the very first VC investment round itself (**H2**).

Trademarks as a Predictor of Successful Private Firm Exit

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

2.3.2 Trademarks as a Signal to IPO Market Investors

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

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

Next, we discuss the relation between the number of trademarks held by a firm and its valuation at the IPO offer price. This relation depends on the process of setting the offer price in IPOs. While there is no consensus in the theoretical and empirical IPO literature on precisely how the IPO offer price is set, this price-setting process can be broadly thought of as the following. During the book-building and road-show process, the lead underwriter conveys information about the IPO firm to institutions (this, in turn, may affect their valuation of the firm). The lead underwriter may also extract information from institutional investors about their valuation of the IPO firm and their demand for the firm's share. Toward the end of the book-building and road-show process, the lead underwriter uses the above information to establish the highest uniform price at which it can sell all the shares offered in the IPO (i.e., the market-clearing price, which is also the underwriter's expectation of the first day secondary market closing price), and then applies a "discount" to the market clearing price, thus establishing the actual IPO offer price (typically on the evening before the IPO). One possible explanation for such a discount is to compensate institutional investors for their cost of producing information about the IPO firm (see, e.g., Chemmanur (1993)).[18] Since trademarks may serve as a signal of intrinsic firm value to institutional investors and reduce their cost of information production, we expect this discount to be smaller for firms which have registered a larger number of trademarks. Consequently, we expect firms with a larger number of trademarks to have a higher IPO market valuations (**H5**).

The Relation between Trademarks and Institutional Investor Participation

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

[18] There are a number of alternative theories in the IPO literature that may explain this IPO discount: see, e.g., Benveniste and Spindt (1989) for another theory based on bookbuilding. Regardless of the underlying theory that may explain the IPO discount, the prediction that the IPO valuation of a firm will be increasing in the number of trademarks registered by the firm at the time of IPO will hold as long as the discount to the market clearing price set by IPO underwriters is not assumed to be increasing in the number of trademarks held by the IPO firm.

2.3.3 Direct Tests of the Protective and the Informational Role of Trademarks

A Direct Test of the Protective Role of Trademarks

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

A Direct test of the Informational Role of Trademarks

We posited earlier that trademarks are positive (but possibly noisy) signals of intrinsic firm value to investors: i.e., they may play an informational role. If this is the case, both institutional and retail investors in the IPO market may have more accurate information about firms which possess a larger number of trademarks. Therefore, we expect firms with a larger number of trademarks to face a smaller extent of information asymmetry in the post-IPO equity market (**H8**). Given that the relation between the number of trademarks and the information asymmetry facing the firm after the IPO is likely to be related only to the informational role of trademarks (i.e., unrelated to the protective role of trademarks), our test of the above hypothesis may be viewed as a direct test of the informational role of trademarks.

2.4 Trademark Applications: Institutional Detail

As per the USPTO website, a trademark life cycle begins with a firm selecting a mark and filing it with the USPTO to be registered as a trademark.[19] Upon filing the application, the USPTO checks for the minimum filing requirements and assigns a serial number to the application provided the application meets the filing criteria. After the assignment, the USPTO appoints an examining attorney to review the application. The USPTO explicitly mentions on their website that applica-

[19] Note that the trademark application and evaluation process is completely distinct from the patent application and evaluation process and is handled by a separate division of the USPTO.

tions are randomly assigned to examining attorneys and are examined in the order in which they are received by the USPTO.[20] The examining attorney performs a complete examination of the application to determine whether the mark is eligible for registration. If the examining attorney believes that the mark meets statutory registration criteria, she will approve the application for publication.[21] Otherwise, she will issue an office action explaining grounds for rejection or suggest minor corrections if required. The most common ground for refusing registration is the existence of a "likelihood of confusion" between the applicant's mark and the mark in an existing registration by another firm.[22] Other grounds for refusal include that the proposed mark is generic or merely descriptive, geographic, a surname, deceptive, among other things.[23] If the examining attorney raises no objections to registration, or if the applicant overcomes all objections, the examining attorney will approve the mark for publication in the "Official Gazette," a weekly publication of the USPTO. The USPTO will send a notice of publication to the applicant stating the date of publication. After the mark is published in the "Official Gazette," any party who believes it may be damaged by the registration of the mark has 30 days from the publication date to file either an opposition to the registration or a request to extend the time to oppose. An opposition is similar to a proceeding in a federal court, but is held before the Trademark Trial and Appeal Board (TTAB), an administrative tribunal within the USPTO. If no opposition is filed or if the opposition is unsuccessful, the application enters the next stage of the registration process.[24] It can take three to four months from the time the notice of publication is sent till the applicant receives an official notice of the next status of the application.

After getting a trademark registration, to keep a registration alive, the registration owner must file required maintenance documents on a regular basis. Failure to file the required maintenance documents during the specified time periods will result in the cancellation of the trademark registra-

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

[21]Unlike in the case of patents, where the examiners specialize in certain areas ("art-units"), the USPTO website mentions that various law offices examining trademarks currently do not specialize in examining trademarks in any particular subject matter.

[22]Likelihood of confusion should only bar registration when the earlier mark is owned by an entity other than applicant.

[23]Please refer Graham, Hancock, Marco, and Myers (2013) for more details.

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

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

2.4.1 Costs Associated with Trademarks

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

Second, there are substantial indirect costs associated with trademark applications and maintenance. There is a substantial cost involved in the trademark opposition process (any person/entity with real interest in the proceedings may oppose a trademark application when it is published for opposition during the application process and attempt to stop it if from registration). Citing the 2013 Report of Economic Survey by the American Intellectual Property Law Association (AIPLA), Gaddis, Garboczi, Stewartson, and Reid (2015) mention that the median cost to a party in trademark opposition is $80,000.[25] Further, this white paper mentions that attorneys' fees are

[25]See more details on trademark opposition cost at: https://tlpc.colorado.edu/wp-content/uploads/2015/05/TMOppositionReform_WhitePaper3.pdf

not recoverable in these cases even if the opposition is frivolous. They claim that frivolous trademark oppositions are a real problem facing small businesses and entrepreneurs, who cannot bear the financial costs of defending an opposition under the current USPTO rules. It is even possible that smaller firms may simply abandon their trademark applications under the threat of opposition. Additionally, it is the responsibility of the firm to enforce its trademark rights by monitoring unfair usage of its trademarks by rivals, which may involve substantial monitoring and potential litigation costs. According to the 2013 American Intellectual Property Law Association ("AIPLA") Report of the Economic Survey, total costs of trademark infringement litigation on average are as follows: $375,000 through trial when less than $1 million is at issue; $794,000 when $1-10 million is at issue; $1.4 million when $10-25 million is at issue; and $2 million in costs when the amount at issue exceeds $25 million.[26]

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

2.5 Data and Sample Selection

2.5.1 Sample Selection

We obtain data on VC-backed private firms in the U.S. from Thomson One VentureXpert. We retrieve round-level information on VC investments in entrepreneurial firms that received their first and last round of investment between January 1, 1990 and December 31, 2010. We use the

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

Thomson One Global New Issues database and Thomson One Mergers and Acquisitions database to obtain information on IPOs and acquisitions, respectively. We exclude firms that received their first round of VC investment after their IPO, which leaves us with 24,512 distinct entrepreneurial firms in the U.S. We identify lead VC investor for each entrepreneurial firm following Nahata (2008) and use VentureXpert to extract their respective age and fund size. After dropping observations with missing data on lead VC or other relevant firm characteristics, we are left with a sample of 13,989 VC-backed private firms. We obtain the trademark data from the USPTO website. We use the 2006 edition of the National Bureau of Economic Research (NBER) Patent Citation database (see Hall, Jaffe, and Trajtenberg (2001) for details) for information on patent applications and grants as well as their respective forward citations. We augment this dataset with patent data from the Harvard Patent Network Dataverse, which contains patent and citation information till 2010. Finally, we use the USPTO website to obtain patent data from 2011 to 2015. Panel A, Panel B, and Panel C of Table 1 provide summary statistics for our sample of VC-backed private firms.

In the second half of our paper, we shift our focus toward VC-backed firms that eventually went public. Out of the 24,512 entrepreneurial firms, 2,106 firms had achieved successful exits via IPOs. Accounting data comes from the Compustat and stock price data comes from the Center for Research in Security Prices (CRSP). We obtain underwriter reputation data from Professor Jay Ritter's website (https://site.warrington.ufl.edu/ritter/ipo-data/). After excluding missing data and merging the above datasets, we are left with a sample of 1,048 public firms. We obtain institutional shareholders' information from the Thomson Reuters Institutional Holdings (13 F) database. Analyst coverage data comes from the Institutional Brokers' Estimate System (I/B/E/S) database. Panel D of Table 1 provides summary statistics for our sample of VC-backed firms that eventually went public.

2.5.2 Measures of Trademarks

We obtain the list of all the trademark applications available in the USPTO database (USPTO trademark case file dataset) from 1982 to 2015.[27] This includes all the applications whether they were granted (i.e., registered trademarks), pending, or abandoned (application that is no longer

[27] Graham, Hancock, Marco, and Myers (2013) notes that the coverage of trademark applications is comprehensive after 1982 in the USPTO case file dataset.

pending and, thus, cannot mature into registration). The case files also contain the names of examining attorneys who examine the trademark applications. We match the trademark dataset with the VentureXpert dataset using the firm name as identifier and adopt a similar matching technique to the one used in the NBER Patent Project. We assume that a VC-backed firm does not have any trademark if we cannot match its name against the trademark dataset. For a particular firm, we count the number of trademarks it has registered from five years prior to receiving the first round of VC investment to the year of concern, which in our study is either the year of receiving the first round of VC investment or the year of exit. We do this to maintain the same event time window for all firms. Following Faurel, Li, Shanthikumar, and Teoh (2016), we use the registration year of trademarks for constructing our measure of trademarks. We use a log measure (*Ln(1 + No. of Trademarks)*) to capture the value of trademarks for a particular firm. We take the natural logarithm because the distribution of trademarks is skewed. We add one to the actual values to avoid losing observations with zero trademark. Panel A of Table 1 reports summary statistics for the trademark measure at the time of the first round of VC investment. Panel D of Table 1 reports summary statistics of trademarks for public firms at time of IPO. Finally, Panel E of table 1 provides summary statistics of trademark applications and trademark examiners.

2.5.3 Measures of Innovation

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

Patent data is subject to two types of truncation problems. First, patents are included in the dataset only after they are granted and on average there is a two-year lag between a patent application and the eventual grant. Therefore, we observe a smaller number of patents which are granted towards the last few years of our sample period. We address this problem by dividing each patent for each firm-year by the mean number of patents for all firms for that year in the same

3-digit technology class as the patent (Seru (2014)). As suggested in Hall, Jaffe, and Trajtenberg (2001), we consider the application year of a patent for constructing our measures of innovation. The second type of truncation problem pertains to citation count. For a given patent, we count the number of forward citations it has received till 2015. Patents tend to receive citations over a long period of time but not many citations during the initial years. As a result, the citation count of later year patents in our sample will be downward biased. For example, patents filed in 2013 are likely to have a smaller number of forward citations than the ones filed in 2005. We adjust this truncation bias by scaling citations of a given patent by the total number of citations received by all the patents filed in the same 3-digit technology class and year (Seru (2014)). Thus we obtain class-adjusted measure of patents and citations, adjusted for trend in innovation activity in a particular technology class as specified by the USPTO.

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

2.5.4 Summary Statistics

Table 1 reports the summary statistics for VC-backed private firms.[28] Panel A shows that an average firm in our sample receives nearly half (54 percent) of the total VC funding in the first round and typically receives three rounds of VC investments. Further, an average firm typically has two VC investors investing in the first round. Around 15.3 percent of firms have at least one trademark in the five years before receiving the first round of VC investment, while 14.6 percent

[28] Note that all the variables are winsorised at the 1st and 99th percentile.

of firms have at least one patent, and 3.5 percent of firms have both patent(s) and trademark(s). However, as we show in Panel C, a significant number of firms have patents and trademarks by the time of exit (IPO or acquisition or write-off): 47.4 percent of firms have at least one trademark and 28.6 percent of firms have at least one patent. Around 20 percent of firms have both patent(s) and trademark(s) at the time of exit.

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

Lastly, in Panel E, we present the summary statistics of trademark applications and registered trademarks for firms at the time of exit. We compute lag between filing of a trademark and actual outcome from a data of around 6 million trademark applications from 1982 to 2015 available on the USPTO website. Trademark applications take around 600 days on average from filing to final outcome. The median lag is 480 days. In total there are 1043 different examining attorneys (examiners) who review trademark applications.[30] We compute an yearly measure of their leniency or the percentage of applications approved by them. The average examiner approval rate if around 54 percent. We also measure the number of trademark applications filed and registered by a firm in a two year period before exit. An average firm files around four trademark applications in the two year period before exit or write-off.

2.6 Empirical Analyses and Results

2.6.1 Methodology and Identification

We empirically test for relation between trademarks and VC investment patterns, successful exit of VC-backed firms, IPO, and post-IPO characteristics. We first use ordinary least square regres-

[29] If a VC-backed firm did not receive any VC investment in the five years after the last VC-investment, we treat it as a case of "no exit" or consider it as an equivalent to a write-off.

[30] We only consider examiners who have reviewed a minimum of 10 applications in a given year.

sions (OLS) to establish correlation between trademarks and the above mentioned firm outcomes. However, it may be argued that the relations we have established so far using our baseline analyses between a larger number of trademarks and various private firm and IPO characteristics are the result of omitted variables: for example, a higher quality private firm may apply for and receive a larger number of trademarks, so that the relations that we documented above between the number of trademarks and the probability of successful private firm exit may be the result of higher firm quality rather than the number of trademarks held by the firm. In other words, the unobservable firm quality may be driving our results. To address this concern, we conduct an IV analysis making use of the random assignment of trademark applications to trademark examining attorneys and the exogenous source of variation in attorney leniency in approving trademark applications.[31] Our IV analysis approach builds on similar applications in the literature.[32] We describe the construction of our instrument in detail in the next subsection.

2.6.2 Instrumental Variable: Average Examiner Leniency

We use average examiner leniency as an instrument for the number of trademarks granted to a firm. As mentioned earlier in section 4, the USPTO website has a documentation describing the trademark dataset where it is stated that trademark applications are randomly assigned to trademark examining attorneys (examiners), who review these applications in the order in which they are received by the USPTO, and the examiners determine whether registration of these applications are permissible by federal law. A generic or merely descriptive mark will be rejected and so will be a mark that can create a "likelihood of confusion" with an existing trademark.[33] Therefore, a degree of subjectivity and examiner discretion is involved in the examination process of trademark applications, and we exploit this discretion in our IV analysis. We realize that applying for trademarks is an endogenous choice of a firm. There may be some firms that are able to apply for trademarks but choose not to do so. Therefore, in our IV analyses, we only focus on firms that have applied for trademarks (with varying degrees of success). In other words, for our IV analysis,

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

[32] Maestas, Mullen, and Strand (2013) exploit the variation in allowance rate of disability insurance examiners to show the disincentive effect of benefits. Sampat and Williams (2019) and Farre-Mensa, Hegde, and Ljungqvist (2019) use patent examiner leniency as an instrument for patent grants in their research.

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

we consider firms that have made at least one trademark application. The success rate of a trademark application will depend on the quality of the application and the leniency of examiner.[34] An application assigned to a more lenient examiner will be more likely to be approved compared to an application of similar quality assigned to a less lenient examiner. Our IV analyses exploit the exogenous variation in leniency of trademark examiners (randomly assigned) that affect the outcome of trademark applications. Further, the leniency of examiner is unlikely to be correlated with either firm or trademark quality.[35] As mentioned in the data section, we have information on the applications, their outcomes, and corresponding examiners from the trademark case files available on the USPTO website. We compute a time-varying measure of the leniency of each individual examiner. Specifically, the approval rate of examiner j assigned to review a trademark application k made by a firm i in year t is defined as follows:

$$Individual\ Examiner\ Leniency_{ijkt} = \frac{Grants_{jt} - Grant_k}{Applications_{jt} - 1}, \tag{2.1}$$

where $Grants_{jt}$ and $Applications_{jt}$ are the numbers of trademark granted and applications reviewed, respectively, by examiner j in the same application year as application k.[36] $Grant_k$ denotes the outcome of an application k and takes the value 1 if the application is approved and 0 otherwise. Intuitively, the empirical setup follows prior research on examiners that leaves out the application itself while computing the examiner approval rate.[37] Since we are interested in obtaining an instrument for the number of trademarks granted to a firm, we average examiner leniency across applications. We consider all the trademark applications filed by a firm in the two-year window prior to its successful exit (IPO or acquisition).[38] We then compute the average examiner leniency for a firm over the two-year window as the instrument for the number of trademarks registered by the firm. Specifically, we compute our instrument, i.e., the average examiner leniency (*Avg*

[34] By quality of application, we refer to the information provided by applicant in the application, which may help distinguish its mark from existing mark owned by other entities.

[35] We show in Table A1 that our examiner leniency measure is uncorrelated with firm characteristics.

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

[37] See, e.g., Maestas, Mullen, and Strand (2013)

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

Leniency$_{it}$) for a firm i in year t, as follows:

$$\textit{Avg Leniency}_{it} = \frac{1}{n_i}\sum_j \textit{Individual Examiner Leniency}_{ijkt}, \tag{2.2}$$

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

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

$$\textit{Ln(1+No. of Trademarks)}_{it} = \alpha_1 \textit{Avg Leniency}_{it} + \alpha_2 \textit{Applications}_{it} + \alpha_3 X_{it} + \epsilon_{it}. \tag{2.3}$$

$$\textit{Outcome}_{it} = \beta_1 \widehat{\textit{Ln(1+No. of Trademarks)}}_{it} + \beta_2 \textit{Applications}_{it} + \beta_3 X_{it} + \epsilon_{it}. \tag{2.4}$$

In the first-stage regression (equation (3)), we regress *Ln(1+No. of Trademarks)$_{it}$* on the instrument (*Avg Leniency$_{it}$*), i.e., 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 two-year window. *Applications$_{it}$* is the number of trademark applications filed in the two-year window and X_{it} is a vector of controls used in prior tests.[40] Equation (4) presents the second stage of our IV (2SLS) regressions, where we regress different outcome variables (*Outcome$_{it}$*) on the predicted value of the natural logarithm of one plus the total number of trademarks, computed from the first stage.

Instrument Relevance

We make use of a subsample of 5,925,040 trademark applications filed from 1982 to 2015, for which we have examiner information available. We only consider examiners who have examined more than 10 applications in a year. Figure 1 shows the distribution of examiners' yearly approval rates (as defined in equation (1)), from which we observe significant variation in the examiners' approval rates: the median examiner yearly approval rate is 56 percent and the interquartile range is 11.6 percent.

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

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

Exclusion Restriction

In order to satisfy the exclusion restriction, our instrumental variable should affect the outcome variables (including VC-backed private firm and IPO characteristics) only through its relation with the endogenous variable, i.e., the number of trademarks registered by a firm in the two-year window prior to the successful exit. Angrist and Pischke (2008) argue that for an instrument to satisfy the exclusion restriction, the following two conditions must hold: First, the instrument should be randomly assigned, i.e., independent of potential outcomes, conditional on covariates; second, the instrument should have no effect on outcomes other than through the first-stage channel. In our analyses, the first condition is satisfied since the trademarks applications are randomly assigned to examiners, irrespective of the quality of an application. We also show in Table A1 in our appendix that our instrument, trademark examiners' leniency, is uncorrelated with firm, investor, and investment characteristics. Further, applicants do not know the identity of trademark examiners when the USPTO assigns applications to trademark examiners. Applicants become aware of the identity of examiners only *ex-post* when either their application is approved or they receive an office action explaining the grounds for refusal and/or possible options for responding to the refusal. Since a firm does not know the identity of its application examiner *ex-ante*, they cannot take actions which may affect the outcome variables in the period between the assignment of an application to an examiner and the outcome of the application. In summary, our instrument satisfies the exclusion restriction as well.[41]

[41] One may be concerned about the use of average examiner leniency as our instrument, since a firm may keep resubmitting a rejected trademark application by making slight changes in each new application. If this is the case, one would expect to find a positive correlation between the leniency of the examiner of a firm's first application and

2.6.3 The Effect of Trademarks on the Pattern of Investment by VCs

In the following subsections, we present and discuss our baseline analyses on the relation between trademarks held by VC-backed firms and VC investment patterns.

Baseline Analysis

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

$$Var_{it} = \alpha_0 + \alpha_1 \mathit{Ln(1\ +\ No.\ of\ Trademarks)}_{it} + X_{it} + \epsilon_{it}, \tag{2.5}$$

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

We use either class-adjusted patents (*Ln(1+No. Patents)*) or citations (*Ln(1+No. Citations)*) to control for the effect of firm-innovation on VC investment size or staging. We control for the age of a private firm (*Ln(1+Firm Age)*), the number of VC investors in the first round (*Syndicate Size*), the age of the lead VC (*Ln(1+VC Age)*), and the fund size of the lead VC (*Ln(VC Fund*

its subsequent applications. However, in an untabulated analysis, we find that this is not the case: we do not find any correlation between the examiner leniency of the first trademark application of a firm and its subsequent trademark applications. Furthermore, we show in Table A1 that average examiner leniency is uncorrelated to firm or investor characteristics, thus ruling out the above concern.

Size)). We include fixed effects for industry, year, state of firm headquarters, and the lead VC in our regressions to account for heterogeneity due to these factors. We cluster standard errors at the lead VC level since residuals may be correlated across observations backed by the same lead VC.

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

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

2.6.4 The Effect of Trademarks on Successful Private Firm Exit

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

Baseline Analysis

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

$$Exit_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \tag{2.6}$$

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

In the above regressions, we control for firm innovation using either class-adjusted patents or citations since it may affect the probability of a firm's successful exit. Following the existing literature (see, e.g., Tian (2011)), we include a set of other control variables in our regressions such as the age of a private firm, total VC investments, the age of the lead VC, fund size of the lead VC, the total number of rounds of VC investments, and the average number of VC investors per round.[42] We include in the regressions dummy variables for industry, year of last round of VC investment, firm-headquarters state, and lead VC, respectively, and cluster standard errors at the lead VC level.

We present our results of the above regressions in Table 3. In Columns (1) and (2), we use IPO and acquisition dummy as the dependent variable. We find that the coefficients of trademarks are positive and significant at the 1 percent level. In Columns (3) and (4), we use the IPO dummy as the dependent variable. We find that, here also, the coefficients of trademarks are positive and significant (at the 1 percent level) in Column (4). Finally, in Columns (5) and (6), we use the acquisition dummy and find that the coefficients of trademarks are positive and significant at the 1 percent level. Our results are also economically significant: a one standard deviation increase in our trademark measure is associated with a 3.1 percentage point, 0.68 percentage point, and 3.1 percentage point increase in the probability of a successful exit by either IPO and M&A, IPO only, and M&A only, respectively. These results suggest that firms with a larger number of trademarks are associated with a greater chance of successful exit, which supports our hypothesis **H3**.

Instrumental Variable Analysis

Here, we run a two-stage linear probability regression model (similar to the two stage tests shown in equations (3) and (4)) and use measures of successful exits as the dependent variable in the second stage. Note that our baseline and instrumental variable analyses are robust to using a probit model. We include the same controls and dummy variables as in our corresponding baseline linear probability regressions. We also include an additional control, i.e., the number of applications ($Applications_{it}$) in both stages, to control for the fact that a firm with more applications may likely have more registered trademarks.

We report the results of these regressions in Table 4.[43] In Column (1), we report the first-stage

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

[43] The sample size for our IV analyses is smaller than our OLS analyses, since it contains firms that have made at least one trademark application. Our OLS analysis, which provide external validation, include all firms irrespective

regression result of our IV analysis, which corresponds to successful exit through IPO or acquisitions (corresponding second stages shown in Columns (2) and (3)). We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 29.60 and the adjusted R-squared is 25.7 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. Corresponding first stage results for other two measures of successful exit (IPO only and M&A only) satisfy the relevance condition, but are suppressed in the table. We report the second-stage regression results in Columns (2) to (7). In Columns (2) and (3), the dependent variable is a dummy variable for IPOs and acquisitions (*IPO and M&A*). We find that the coefficients of the trademark measure are positive and significant at the 1 percent level. In Columns (4) and (5), the dependent variable is a dummy variable for IPOs (*IPO only*). The coefficients of the trademark measure are positive but insignificant. Finally, in Columns (6) and (7), the dependent variable is a dummy variable for acquisitions (*M&A only*). We find that the coefficients of the trademark measure are positive and significant at the 1 percent level. Thus, our IV analysis results show that the positive relation between trademarks on the likelihood of successful exits of VC-backed private firms is causal, which lends strong support to our hypothesis **H3**.

2.6.5 The Effect of Trademarks on IPO and Secondary Market Valuations

We conduct baseline and instrumental variable analyses to study the relation between trademarks and IPO and secondary market valuations of VC-backed private firms going public.

Baseline Analysis

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

$$Valuation_{it} = \alpha_0 + \alpha_1 Ln(1\ +\ No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \tag{2.7}$$

of them having trademarks or not.

where i denotes the firm and t denotes the year of IPO. We construct our valuation measures using Tobin's Q, which is the ratio of market value of assets over the book value of assets.[44] We measure IPO market valuation using the IPO offer price. We measure secondary market valuation using two different measures: using first trading day closing price as the share price and using the share price at the end of the first post-IPO fiscal quarter. We construct Tobin's Q ratios for our three valuation measures, *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation(FQ)*.[45] X represents a vector of controls, which are described below.

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

We present our results of the above tests in Table 5. In Columns (1) and (2), the dependent variable is IPO valuation. We find that the coefficients of trademarks are positive and significant (at the 1 percent level). In Columns (3) and (4), the dependent variable is secondary market valuation computed using first day closing price. The coefficients of trademarks in these regressions are positive and significant (at the 5 percent level). Finally, in Columns (5) and (6), our dependent variable is the secondary market valuation computed using first post-IPO fiscal quarter share price.[46] Here also, the coefficients of trademarks are positive and significant at the 5 percent and 1 percent level, respectively. Our results are also economically significant: a one standard deviation increase in our trademark measure is associated with an increase of 0.31, 0.37, and 0.58 for *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* respectively. These increases are equivalent to 8 percent, 7.3 percent, and 10.2 percent average increase in *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)*, respectively. In sum, our empirical results

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

[45] The book value of assets and the book value of equity for IPO firms are taken from the first available post-IPO quarter on Compustat. The number of shares outstanding for IPO firms is measured as of the first trading day.

[46] If we remove trademarks as the main independent variable, we find that the coefficients of patents are positive and significant. However, the correlation between trademarks and patents is small, around 0.2.

presented in this subsection show that firms with a larger number of trademarks are associated with larger IPO and immediate secondary market valuations, which supports our hypotheses **H5** and **H4**, respectively.

Instrumental Variable Analysis

We report our IV regression results of the effects of trademarks on IPO and secondary market valuations in Table 6. In Column (1), we present the first-stage regression results of our IV analysis, which corresponds to IPO valuations (corresponding second stages shown in Columns (2) and (3)). We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 43.799 and the adjusted R-squared is 22.2 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. Corresponding first stage results for the two measures of secondary market valuations satisfy the relevance condition, but are suppressed in the table. We present the second-stage regression results in the Columns (2)-(7). In Columns (2) and (3), we use a firm's IPO valuation (*IPO Valuation*) as the dependent variable and find that the coefficients of our trademark measure are positive and significant at 10 percent level (in Column (3)). In Columns (4) and (5), we use a firm's secondary market valuation computed using first day closing price (*Secondary Valuation (FD)*) as the dependent variable and find that the coefficients of our trademark measure are positive and significant at the 1 percent level. Finally, in Columns (6) and (7), we use the secondary market valuation computed using first post-IPO fiscal quarter price (*Secondary Valuation (FQ)*) as the dependent variable and find that the coefficients of our trademark measure are positive and significant (at 5 percent level in Column (7)). Thus, our IV analysis results show that trademarks have a positive and causal effect on firm valuation, which supports our hypothesis **H4**.

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

We conduct baseline and instrumental variable analyses to study the relation between trademarks and the participation of institutional investors in a firm's IPO.

Baseline Analysis

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

$$MP_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \tag{2.8}$$

where i denotes the firm and t denotes the year of IPO. We use the natural logarithm of one plus the total number of institutional investors holding shares in a firm (*Ln(1+No. of Institutional Investors)*) as the dependent variable. The explanatory variable of interest in our regressions is our trademark measure. X represents a vector of controls, which are described below. We control for firm innovation using either class-adjusted patents or citations since they may affect the participation of institutional investors. Following the existing literature (see, e.g., Bajo, Chemmanur, Simonyan, and Tehranian (2016)), our other control variables include underwriter reputation, firm size, total IPO proceeds, firm age, underpricing, and Tobin's Q.[47] We include fixed effects for industry, year, and firm-headquarter state in our regressions and cluster standard errors at the two-digit SIC code industry level.

We present our empirical results of the above regressions in Table 7. In Columns (1) and (2), we find that the coefficients of trademarks are significant at the 10 percent level. Our results are also economically significant: a one standard deviation increase in our trademark measure is associated with a 0.2 percent increase in the number of institutional investors investing in the firm. These results suggest that firms with a larger number of trademarks are associated with greater institutional investor participation, which supports our hypothesis **H6**.

Instrumental Variable Analysis

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

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

our IV analysis. We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 51.714 and the adjusted R-squared is 20.4 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. We present the second-stage regression results in Columns (2) and (3), in which the dependent variable is the natural logarithm of one plus the number of institutional investors investing in the IPO firm (*Ln(1+No. of Institutional Investors)*). We find that the coefficients of our trademark measure are positive and significant at the 10 percent level. Thus, our IV analysis results confirm that trademarks have a positive and causal effect on institutional investor participation in an IPO firm, which supports our hypothesis **H6**.

2.6.7 The Effect of Trademarks on Post-IPO Operating Performance

We conduct baseline and instrumental variable analyses to study the relation between trademarks and the post-IPO operating performance of VC-backed private firms going public.

Baseline Analysis

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

$$OP_{it} = \alpha_0 + \alpha_1 \mathit{Ln(1\ +\ No.\ of\ Trademarks)}_{it} + X_{it} + \epsilon_{it}. \tag{2.9}$$

In the above model, the dependent variable OP_{it} is the operating performance measure, and i denotes the firm and t denotes the year of IPO. We measure post-IPO operating performance using *OIBDA*, the ratio of operating income before depreciation plus interest income (Compustat item 13 and 62, respectively) to the book value of total assets (item 6): see, e.g., Jain and Kini (1994) and Loughran and Ritter (1997).[48] This measure is constructed for the following four years post-IPO (i.e., year 1, 2, 3, and 4). The explanatory variable of interest in our regressions is our trademark measure. X represents a vector of controls, which are described below. We control for firm innovation using either class-adjusted patents or citations since they may have

[48] Our results are robust to adjusting the operating performance of a firm with respect to its respective industry operating performance.

an impact on operating performance. Our other control variables include underwriter reputation (*Ln(Underwriter Reputation)*), firm size (*Ln(Assets)*), firm age (*Ln(1+Firm Age)*), and *Tobins' Q*. We include fixed effects for industry, year, and state of firm headquarters in our regressions and cluster standard errors at the two-digit SIC code industry level.

We present our results of the above tests in Table 9. We find that for the three years after IPO, the coefficients of trademarks are positive and significant (in Columns (1) to (6)). For the year 4 after IPO, the results are in the right direction but are not significant. In terms of economic magnitude, a one standard deviation increase in our trademark measure is associated with an increase of 0.051 in *OIBDA* in the first year after IPO. This increase is substantial, given that the mean value of *OIBDA* in the first year after IPO is -0.15. In sum, our results presented in this section suggest that firms with a larger number of trademarks are associated with better post-IPO operating performance, which supports our hypothesis **H7**.

Instrumental Variable Analysis

We report our IV regression results of the effect of trademarks on a firm's post-IPO operating performance in Table 10. We report the second-stage results in Columns (1)-(8).[49] In Columns (1)-(8), we use *OIBDA* in the years 1, 2, 3 and 4 after IPO as dependent variables. We find that the coefficients of our trademark measure are positive and significant at the 10 percent level for the post-IPO operating performance in year 3 and year 4 (Columns (5), (6) and (7)). Broadly, our IV analysis results suggest that trademarks play a protective role, i.e., firms with a larger number of trademarks have better post-IPO operating performance, which supports our hypothesis **H7**.

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

We conduct baseline and instrumental variable analyses to study the relation between trademarks and the information asymmetry facing the firm in the IPO market.

[49]Due to space limitations, we do not post the first stage results. However, our first stage results are relevant and significant.

Baseline Analysis

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

$$Asymmetry_{it} = \alpha_0 + \alpha_1 Ln(1 + No.\ of\ Trademarks)_{it} + X_{it} + \epsilon_{it}, \tag{2.10}$$

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

We present our results of the above tests in Table 11. In Columns (1) and (2), we use the analyst forecast error as the dependent variable and find that the coefficients of trademarks are negative but insignificant. In Columns (3) and (4), we use the analyst forecast dispersion as the dependent variable and find that the coefficients of trademarks are negative and significant at the 10 percent level. In Columns (5) and (6), we use the number of analysts covering the firm as the dependent variable and find that the coefficients of trademarks are positive and significant at the 10 percent and 5 percent level, respectively. These results suggest that firms with a larger number of trademarks are associated with a smaller extent of information asymmetry in the equity market, which supports our hypothesis **H8**. Our results are also economically significant. For example, a one standard deviation increase in our trademark measure is associated with a reduction of 0.09

in *Dispersion*, which is equivalent to a 21.1 percent reduction in the average *Dispersion*. Also, a one standard deviation increase in our trademark measure is associated with an increase of 0.23 in number of analysts covering a firm, which is equivalent to a 6 percent increase in the average *No. of Analysts*.

Instrumental Variable Analysis

We report our IV regression results of the effect of trademarks on the information asymmetry facing the firm in the post-IPO market in Table 12. In Column (1), we present the first-stage regression results of our IV analysis, which corresponds to forecast error as a measure of information asymmetry (corresponding second stages shown in Columns (2) and (3)). We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant (at the 1 percent level). The first-stage F-statistic is 34.87 and the adjusted R-squared is 30.8 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. Corresponding first stage results for the other two measures of information asymmetry, analyst dispersion and the number of analysts following a firm, satisfy the relevance condition, but are suppressed in the table. We report the second-stage regression results in Columns (2)-(7). In Columns (2) and(3), we use the analyst forecast error (*Forecast Error*) as the dependent variable and find that the coefficients of our trademark measure are negative and significant at the 5 percent level. As for regressions using the other two measures of information asymmetry (*Dispersion* and *No. of Analysts*) as dependent variables, our results are in the right direction but insignificant. Broadly, our results suggest that trademarks play an informational role, i.e., firms with larger number of trademarks face a lower extent of information asymmetry in the equity market, which supports our hypothesis **H8**.

2.7 Conclusion

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

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

References

Aggarwal, Rajesh K, Laurie Krigman, and Kent L Womack, 2002, Strategic IPO underpricing, information momentum, and lockup expiration selling, *Journal of Financial Economics* 66, 105–137.

Angrist, Joshua D, and Jörn-Steffen Pischke, 2008, *Mostly harmless econometrics: An empiricist's companion* (Princeton university press).

Bajo, Emanuele, Thomas J. Chemmanur, Karen Simonyan, and Hassan Tehranian, 2016, Underwriter networks, investor attention, and initial public offerings, *Journal of Financial Economics* 122, 376 – 408.

Benveniste, Lawrence M, and Paul A Spindt, 1989, How investment bankers determine the offer price and allocation of new issues, *Journal of financial Economics* 24, 343–361.

Besen, Stanley M, and Leo J Raskind, 1991, An introduction to the law and economics of intellectual property, *Journal of Economic Perspectives* 5, 3–27.

Bhattacharya, Sudipto, and Jay R Ritter, 1983, Innovation and communication: Signalling with partial disclosure, *The Review of Economic Studies* 50, 331–346.

Block, Joern H., Geertjan De Vries, Jan H. Schumann, and Philipp Sandner, 2014, Trademarks and venture capital valuation, *Journal of Business Venturing* 29, 525–542.

Cao, Jerry, Fuwei Jiang, and Jay R Ritter, 2013, Patent and Innovation-Driven Performance in Venture Capital-Backed IPOs, Working Paper, University of Florida.

Chemmanur, Thomas, and An Yan, 2009, Product market advertising and new equity issues, *Journal of Financial Economics* 92, 40 – 65.

Chemmanur, Thomas J., 1993, The Pricing of Initial Public Offerings: A Dynamic Model with Information Production, *The Journal of Finance* 48, 285–304.

Chemmanur, Thomas J, and Zhaohui Chen, 2014, Venture capitalists versus angels: The dynamics of private firm financing contracts, *The Review of Corporate Finance Studies* 3, 39–86.

Chemmanur, Thomas J, Manish Gupta, and Karen Simonyan, 2016, Management Quality and Innovation in Private Firms and the IPO Market Rewards to Innovative Activity, Working Paper, Boston College.

Chemmanur, Thomas J, Jie He, Shan He, and Debarshi Nandy, 2018, Product market characteristics and the choice between ipos and acquisitions, *Journal of Financial and Quantitative Analysis* 53, 681–721.

Chemmanur, Thomas J, Shan He, and Debarshi K Nandy, 2009, The going-public decision and the product market, *The Review of Financial Studies* 23, 1855–1908.

Chemmanur, Thomas J, Elena Loutskina, and Xuan Tian, 2014, Corporate venture capital, value creation, and innovation, *The Review of Financial Studies* 27, 2434–2473.

Chemmanur, Thomas J., and Imants Paeglis, 2005, Management quality, certification, and initial public offerings, *Journal of Financial Economics* 76, 331 – 368.

Economides, Nicholas S, 1988, The economics of trademarks, *Trademark Rep.* 78, 523.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist, 2017, What is a Patent Worth? Evidence from the US Patent Lottery, Working Paper, National Bureau of Economic Research.

Faurel, Lucile, Qin Li, Devin M Shanthikumar, and Siew Hong Teoh, 2016, CEO Incentives and New Product Development: Insights from Trademarks, Working Paper, University of California, Irvine.

Gompers, Paul, and Josh Lerner, 2000, Money chasing deals? The impact of fund inflows on private equity valuation, *Journal of Financial Economics* 55, 281–325.

Gompers, Paul A., 1995, Optimal Investment, Monitoring, and the Staging of Venture Capital, *The Journal of Finance* 50, 1461–1489.

Graham, Stuart J.H., Galen Hancock, Alan C. Marco, and Amanda Fila Myers, 2013, The USPTO Trademark Case Files Dataset: Descriptions, Lessons, and Insights, *Journal of Economics and Management Strategy* 22, 669–705.

Graham, Stuart JH, Robert P Merges, Pam Samuelson, and Ted Sichelman, 2009, High technology entrepreneurs and the patent system: Results of the 2008 berkeley patent survey, *Berkeley Technology Law Journal* 24, 1255.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, NBER Working Paper 8498.

Heath, Davidson, and Christopher Mace, 2019, The strategic effects of trademark protection, *The Review of Financial Studies* .

Hsu, David H, and Rosemarie H Ziedonis, 2008, Patents as quality signals for entrepreneurial ventures., in *Academy of Management Proceedings*, volume 2008, 1–6, Academy of Management.

Hsu, Po-Hsuan, Kai Li, Yunan Liu, and Hong Wu, 2017, Product Market Dynamics and Mergers and Acquisitions: Insights from the USPTO Trademark Data, Working Paper, University of British Columbia.

Jain, Bharat A., and Omesh Kini, 1994, The Post-Issue Operating Performance of IPO Firms, *The Journal of Finance* 49, 1699–1726.

Landes, William M., and Richard A. Posner, 1987, Trademark Law: An Economic Perspective, *The Journal of Law and Economics* 30, 265–309.

Lerner, Joshua, 1994, Venture capitalists and the decision to go public, *Journal of Financial Economics* 35, 293–316.

Long, Clarisa, 2002, Patent signals, *The University of Chicago Law Review* 625–679.

Loughran, Tim, and Jay R. Ritter, 1997, The Operating Performance of Firms Conducting Seasoned Equity Offerings, *The Journal of Finance* 52, 1823–1850.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand, 2013, Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt, *American Economic Review* 103, 1797–1829.

Mendonça, Sandro, Tiago Santos Pereira, and Manuel Mira Godinho, 2004, Trademarks as an indicator of innovation and industrial change, *Research Policy* 33, 1385–1404.

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

Ritter, Jay R, and Ivo Welch, 2002, A review of IPO activity, pricing, and allocations, *The Journal of Finance* 57, 1795–1828.

Sampat, Bhaven, and Heidi L Williams, 2019, How do patents affect follow-on innovation? evidence from the human genome, *American Economic Review* 109, 203–36.

Seru, Amit, 2014, Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics* 111, 381–405.

Stock, James H., and Motohiro Yogo, 2002, Testing for Weak Instruments in Linear IV Regression, Working Paper 284, National Bureau of Economic Research.

Tian, Xuan, 2011, The causes and consequences of venture capital stage financing, *Journal of Financial Economics* 101, 132–159.

Tian, Xuan, 2012, The role of venture capital syndication in value creation for entrepreneurial firms, *Review of Finance* 16, 245–283.

Tian, Xuan, and Tracy Yue Wang, 2014, Tolerance for failure and corporate innovation, *The Review of Financial Studies* 27, 211–255.

Zhou, Haibo, Philipp G. Sandner, Simon Luca Martinelli, and Joern H. Block, 2016, Patents, trademarks, and their complementarity in venture capital funding, *Technovation* 47, 14 – 22.

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

This table reports summary statistics for the sample of VC-backed private firms in the U.S. between 1990 and 2010 as well as the subsample of VC-backed firms that went public. All variables are winsorised at 1 and 99 percent. Panel A shows summary statistics for VC-backed private firms at the time of receiving their first round of investment from VCs. *Fraction of Investment in Round 1* is the fraction of VC investments received by a private firm in the first round out of the total VC investments across all rounds. *No. of Rounds by VCs* is the total number of rounds of VC investments received by a private firm. *Ln(Investment in Round 1)* is the natural logarithm of the total VC investments received by a private firm in the first round. *Ln(Total Investment)* is the natural logarithm of the total VC investments across all rounds received by a private firm. All investments are in millions of dollars. *No. of Trademarks* is the total number of trademarks that a firm has registered in the five-year period before the first round of VC investment. *No. of Patents* is the total number of patents filed and eventually granted to a firm in the five-year period before the first round of VC investment. *Total No. of Citations* is the total number of forward citations received by these patents. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of receiving the first round of VC investment. *Syndicate Size* is the number of VC firms investing in the first round of investment in a firm. *Ln(1 + VC Age)* is the natural logarithm of one plus the number of years from the founding year of the lead VC to the year of first round of lead VC investment at the private firm. *Ln(VC Fund Size)* is the natural logarithm of fund size (in millions of dollars) of the lead VC at the time of the first round of VC investment in a private firm. Panel B reports the eventual exit status of the firms. We classify a sample firm as *Acquired* if it was acquired by another firm within five years of receiving its last round of VC investment. A sample firm is classified as *Went Public* if it went public within five years of receiving its last round of VC investment. All other firms are classified as *No Exit.* In Panel C, we show the number of patents and trademarks at the time of exit (IPO or acquisition or write-off). *No. of Trademarks* is the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of exit. *No. of Patents* is the total number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of exit. *Total No. of Citations* is the total number of forward citations received by these patents. The sample in Panel D consists of VC-backed private firms, between 1990 and 2010, which had IPOs within 5 years of receiving the last round of VC investment. *IPO Valuation*, *Secondary Valuation (FD)*, and *Secondary Valuation (FQ)* are the Tobin's Q ratios calculated using the IPO offer price, the first trading day close price, and the price at the end of the first post-IPO fiscal quarter, respectively. Tobin's Q is the ratio of the market value of assets to the book value of the assets, with the market value of assets equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day. The share price we use is the IPO offer price for *IPO Valuation*, the first trading day closing price for *Secondary Valuation (FD),* or the price at the end of first post-IPO fiscal quarter for *Secondary Valuation (FQ)*. *No. of Analysts* is the number of analysts following a firm at the end of the fiscal year of the IPO. *No. of Institutional Investors* is the number of institutional investors holding IPO firm shares at the end of first fiscal quarter after the IPO. *No. of Trademarks* is the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *No. of Patents* is the total number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Total No. of Citations* is the total number of forward citations received by these patents. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(IPO Proceeds)* is the natural logarithm of IPO proceeds. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *ROA* is the operating income before depreciation over the book value of assets at the end of fiscal year prior to the IPO. *Tobin's Q* is the *Tobin's Q* computed using the first trading day closing price. Finally, in Panel E, we show summary statistics of examiner leniency and trademark applications made by firms. *Application Lag (days)* is the number of days between filing of an application and outcome (registration or abandonment of application). We report this statistic for the entire universe of trademark applications filed between 1982 and 2015. *Examiner Leniency (Annual)* is the yearly measure of examiner leniency described in equation (1). *Number of Applications (Exit)* is the total number of trademark applications made by VC-backed private firms in two years before the exit year. *Number of Trademarks (Exit*) is the number of trademarks granted in the two years prior to exit year of the firm. *Number of Applications (IPO)* is the total number of trademark applications made by VC-backed private firms in two years before the IPO year. *Number of Trademarks (IPO)* is the number of trademarks granted in the two years prior to IPO year of a firm.

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

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

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

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

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

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

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

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

Variables	(1) Ln(Investment in Round 1)	(2) Ln(Investment in Round 1)	(3) Ln(Total Investment)	(4) Ln(Total Investment)
Ln(1 + No. of Trademarks)	0.136***	0.146***	0.043	0.064**
	(0.025)	(0.025)	(0.028)	(0.028)
Ln(1 + Firm Age)	0.172***	0.176***	-0.096***	-0.089***
	(0.015)	(0.015)	(0.015)	(0.015)
Syndicate Size	0.277***	0.278***	0.172***	0.175***
	(0.008)	(0.009)	(0.008)	(0.009)
Ln(1 + VC Age)	-0.072	-0.075	-0.058	-0.063
	(0.058)	(0.058)	(0.057)	(0.058)
Ln(VC Fund Size)	0.283***	0.284***	0.139***	0.139***
	(0.043)	(0.044)	(0.039)	(0.039)
Ln(1 + No. of Patents)	0.204***		0.340***	
	(0.038)		(0.045)	
Ln(1 + No. of Citations)		9.805***		11.840***
		(2.860)		(3.724)
Observations	11,676	11,676	11,676	11,676
Adjusted R-squared	0.423	0.422	0.381	0.378
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lead VC FE	Yes	Yes	Yes	Yes

Panel B: The Effect of Trademarks on the Staging of VC Investment				
	(1)	(2)	(3)	(4)
Variables	Fraction of Investment in Round 1	Fraction of Investment in Round 1	No. of Rounds by VCs	No. of Rounds by VCs
Ln(1 + No. of Trademarks)	0.035***	0.030***	-0.237***	-0.210***
	(0.008)	(0.008)	(0.049)	(0.049)
Ln(1 + Firm Age)	0.072***	0.071***	-0.317***	-0.307***
	(0.004)	(0.004)	(0.027)	(0.027)
Syndicate Size	0.008***	0.007***	0.059***	0.063***
	(0.002)	(0.002)	(0.018)	(0.018)
Ln(1 + VC Age)	0.006	0.006	0.042	0.038
	(0.013)	(0.013)	(0.103)	(0.103)
Ln(VC Fund Size)	0.019**	0.019**	-0.070	-0.070
	(0.009)	(0.009)	(0.066)	(0.066)
Ln(1 + No. of Patents)	-0.062***		0.398***	
	(0.012)		(0.081)	
Ln(1 + No. of Citations)		-0.710		8.314
		(1.001)		(6.909)
Observations	11,676	11,676	11,676	11,676
Adjusted R-squared	0.332	0.330	0.262	0.261
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Lead VC FE	Yes	Yes	Yes	Yes

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

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

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage
Variables	Ln (1+ No. of Trademarks)	IPO and M&A	IPO and M&A	IPO only	IPO only	M&A only	M&A only
Examiner Leniency	0.739***						
	(0.129)						
Predicted Ln (1+ No. of Trademarks)		0.685***	0.679***	0.077	0.088	0.922***	0.917***
		(0.193)	(0.192)	(0.149)	(0.148)	(0.325)	(0.326)
Ln(1 + Firm Age)	0.062***	-0.064***	-0.065***	0.005	0.007	0.019	0.018
	(0.020)	(0.023)	(0.023)	(0.016)	(0.016)	(0.028)	(0.028)
Ln(Total Investment)	-0.017	0.052***	0.050***	0.040***	0.044***	0.030*	0.028
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.018)	(0.018)
Ln(1 + VC Age)	0.028	-0.101*	-0.100	0.024	0.021	-0.095	-0.095
	(0.060)	(0.061)	(0.061)	(0.050)	(0.050)	(0.067)	(0.067)
Ln(VC Fund Size)	0.112***	-0.275***	-0.275***	-0.156***	-0.150***	0.012	0.011
	(0.024)	(0.030)	(0.030)	(0.027)	(0.028)	(0.034)	(0.034)
No. of Rounds by VCs	-0.008	0.011*	0.011*	0.011**	0.012**	0.000	-0.000
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
Average No. of VCs per Round	0.001	0.006	0.005	0.019**	0.019**	-0.019*	-0.019*
	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)	(0.011)	(0.011)
No. of Trademark Applications	0.036***	-0.023***	-0.023***	0.003	0.003	-0.029***	-0.029***
	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)
Ln(1 + No. of Patents)	0.008	-0.017		0.057***		-0.013	
	(0.017)	(0.020)		(0.014)		(0.026)	
Ln(1 + No. of Citations)			0.386		0.947		0.413
			(0.716)		(0.677)		(0.870)
Observations	2808	2,808	2,808	2,808	2,808	2,808	2,808
F Statistic from 1st Stage	29.60						
Adjusted R-squared	0.257						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: The Relation between Trademarks and IPO and Secondary Market Valuations

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

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	IPO Valuation		Secondary Valuation (FD)		Secondary Valuation (FQ)	
Ln(1 + No. of Trademarks)	0.322***	0.339***	0.390**	0.424**	0.606**	0.678***
	(0.078)	(0.080)	(0.174)	(0.155)	(0.244)	(0.224)
Ln(Underwriter Reputation)	0.024	0.028	-0.108	-0.100	0.001	0.049
	(0.125)	(0.131)	(0.228)	(0.221)	(0.230)	(0.218)
Ln(Assets)	-0.393***	-0.396***	-0.892***	-0.897***	-0.821***	-0.829***
	(0.075)	(0.076)	(0.183)	(0.180)	(0.207)	(0.211)
Ln(IPO Proceeds)	0.282	0.294*	2.184***	2.206***	1.953***	1.976***
	(0.178)	(0.159)	(0.498)	(0.507)	(0.455)	(0.470)
Ln(1 + Firm Age)	-0.192	-0.193	-0.523***	-0.526***	-0.845***	-0.851***
	(0.203)	(0.199)	(0.185)	(0.180)	(0.233)	(0.243)
ROA	-1.006	-1.035	-1.674	-1.729	-0.978	-1.081
	(0.707)	(0.754)	(1.358)	(1.424)	(1.432)	(1.517)
Ln(1 + No. of Patents)	0.086		0.189		0.556	
	(0.136)		(0.331)		(0.383)	
Ln(1 + No. of Citations)		0.132		0.640		11.502
		(6.081)		(5.620)		(7.817)
Observations	823	823	845	845	883	883
Adjusted R-squared	0.059	0.058	0.182	0.181	0.217	0.215
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Instrumental Variable Analysis of the Relation between Trademarks and IPO and Secondary Market Valuations

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage
Variables	Ln(1+No. of Trademarks)	IPO Valuation		Secondary Valuation (FD)		Secondary Valuation (FQ)	
Examiner Leniency	1.837***						
	(0.278)						
Predicted Ln (1+ No. of Trademarks)		1.178	1.515*	2.859***	3.101***	2.459	3.196**
		(0.965)	(0.868)	(0.960)	(0.938)	(1.490)	(1.428)
Ln(Underwriter Reputation)	0.009	-0.152	-0.130	-0.184	-0.177	0.075	0.154
	(0.059)	(0.264)	(0.294)	(0.360)	(0.365)	(0.313)	(0.330)
Ln(Assets)	0.065***	-0.444***	-0.485***	-1.231***	-1.260***	-1.171***	-1.243***
	(0.023)	(0.150)	(0.159)	(0.274)	(0.276)	(0.333)	(0.346)
Ln(IPO Proceeds)	-0.034	0.550**	0.614**	3.010***	3.051***	2.481***	2.544***
	(0.030)	(0.251)	(0.232)	(0.521)	(0.500)	(0.439)	(0.428)
Ln(1 + Firm Age)	0.002	-0.300	-0.286	-1.041***	-1.039***	-1.490***	-1.492***
	(0.033)	(0.222)	(0.228)	(0.320)	(0.320)	(0.378)	(0.389)
ROA	0.189	-1.697**	-1.843***	-1.240	-1.335	1.014	0.818
	(0.111)	(0.633)	(0.632)	(0.924)	(0.972)	(1.002)	(1.085)
No. of Trademark Applications	0.020	-0.047*	-0.048*	-0.107**	-0.109**	-0.080	-0.087
	(0.012)	(0.025)	(0.024)	(0.042)	(0.041)	(0.057)	(0.062)
Ln(1 + No. of Patents)	0.002	0.375*		0.210		0.711**	
	(0.018)	(0.199)		(0.191)		(0.301)	
Ln(1 + No. of Citations)			1.891		-1.707		11.917
			(9.807)		(9.764)		(14.732)
Observations	495	495	495	510	510	530	530
F Statistics from 1st Stage	43.799						
Adjusted R-squared	0.222						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: The Relation between Trademarks and the Participation of Institutional Investors in a Firm's IPO

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

	(1)	(2)
Variables	Ln(1 + No. of Institutional Investors)	
Ln(1 + No. of Trademarks)	0.061*	0.056*
	(0.030)	(0.029)
Ln(Underwriter Reputation)	0.066	0.067
	(0.056)	(0.058)
Ln(Assets)	-0.012	-0.011
	(0.018)	(0.018)
Ln(IPO proceeds)	0.641***	0.638***
	(0.079)	(0.080)
Ln(1 + Firm Age)	-0.004	-0.004
	(0.029)	(0.029)
Underpricing	0.188***	0.187***
	(0.043)	(0.043)
Tobin's Q	-0.010***	-0.010***
	(0.003)	(0.003)
Ln(1 + No. of Patents)	-0.024	
	(0.033)	
Ln(1 + No. of Citations)		0.009
		(0.992)
Observations	679	679
Adjusted R-squared	0.476	0.476
Industry FE	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes

Table 8: Instrumental Variable Analysis of the Relation between Trademarks and the Participation of Institutional Investors in a Firm's IPO

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

	(1)	(2)	(3)
	First Stage	Second Stage	Second Stage
Variables	Ln(1+ No. of Trademarks)	Ln(1 + No. of Institutional Investors)	
Examiner Leniency	2.096***		
	(0.291)		
Predicted Ln(1+ No. of Trademarks)		0.560*	0.565*
		(0.275)	(0.291)
Ln(1 + No. of Patents)	-0.004	0.025	
	(0.031)	(0.036)	
Ln(1 + No. of Citations)			1.641
			(1.387)
Ln(Underwriter Reputation)	0.040	0.045	0.050
	(0.071)	(0.030)	(0.029)
Ln(Assets)	0.077***	-0.011	-0.010
	(0.026)	(0.038)	(0.038)
Ln(IPO proceeds)	-0.036	0.527***	0.522***
	(0.037)	(0.081)	(0.078)
Ln(1 + Firm Age)	0.013	-0.026	-0.026
	(0.038)	(0.051)	(0.049)
Underpricing	-0.035	0.248***	0.247***
	(0.053)	(0.058)	(0.057)
Tobin's Q	0.008	-0.013**	-0.013**
	(0.006)	(0.006)	(0.006)
No. of Trademark Applications	0.020	-0.018***	-0.018***
	(0.012)	(0.006)	(0.006)
Observations	416	416	416
F Statistic from 1st Stage	51.714		
Adjusted R-squared	0.204		
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Table 9: The Relation between Trademarks and Post-IPO Operating Performance

This table reports the OLS regression results of the effect of trademarks on the post-IPO operating performances of IPO firms. The dependent variable used in this table is *OIBDA* in year 1, 2, 3 and 4, where year 1 is the first year immediately after IPO and year 2, 3, and 4 are corresponding years after the IPO. *OIBDA* is the ratio of operating income before depreciation plus interest income (Compustat items 13 and 62, respectively) to the book value of total assets (item 6). *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered between five years prior to the first round of VC investment and the year of IPO. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Tobin's Q* is the ratio of market and book value of assets computed using the first trading day closing price. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OIBDA							
Variables	Year 1		Year 2		Year 3		Year 4	
Ln(1 + No. of Trademarks)	0.054***	0.052***	0.090***	0.084***	0.117**	0.126**	0.075	0.072
	(0.011)	(0.010)	(0.018)	(0.018)	(0.054)	(0.056)	(0.045)	(0.042)
Ln(Assets)	0.065***	0.065***	0.101***	0.100***	0.154**	0.153**	0.106***	0.106***
	(0.018)	(0.018)	(0.024)	(0.023)	(0.056)	(0.057)	(0.026)	(0.026)
Ln(1 + Firm Age)	0.012	0.013	0.020	0.024	0.189	0.182	0.053	0.058
	(0.047)	(0.047)	(0.034)	(0.037)	(0.117)	(0.114)	(0.065)	(0.064)
Ln(Underwriter Reputation)	0.041***	0.039***	0.048***	0.044***	-0.020	-0.020	0.073	0.073
	(0.010)	(0.011)	(0.006)	(0.008)	(0.052)	(0.052)	(0.076)	(0.077)
Tobin's Q	0.001	0.001	-0.002	-0.002	0.015*	0.015*	-0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.008)	(0.008)	(0.004)	(0.003)
Ln(1 + No. of Patents)	-0.014		-0.038**		0.033		0.003	
	(0.011)		(0.018)		(0.039)		(0.025)	
Ln(1 + No. of Citations)		-0.175		-0.671		0.027		0.527
		(0.569)		(0.553)		(1.516)		(1.136)
Observations	510	510	397	397	317	317	263	263
Adjusted R-squared	0.270	0.269	0.181	0.178	0.045	0.044	0.223	0.224
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Instrumental Variable Analysis of the Relation between Trademarks and Post-IPO Operating Performance

This table reports the instrumental variable regression results of the effect of trademarks post-IPO operating performances of IPO firms. In the first stage regression, we regress *Ln(1+No. of Trademarks)* on *Examiner Leniency* (the instrumental variable), *Ln(Assets), Ln(Underwriter Reputation), Ln(1 + Firm Age), Tobin's Q*, *No. of Trademark applications,* and *Ln(1 + No. of Patents)*. In the second stage regression, we use *Predicted Ln(1+No. of Trademarks)* as the main independent variable. Dependent variable used in this table is *OIBDA* in year 1, 2, 3 and 4, where year 1 is the first year immediately after IPO and year 2, 3, and 4 are corresponding years after the IPO. *OIBDA* is the ratio of operating income before depreciation plus interest income (Compustat items 13 and 62, respectively) to the book value of total assets (item 6). The instrumental variable, *Examiner Leniency*, is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to the IPO. *Ln(1+ No. of Trademarks)* is the natural logarithm of one plus the total number of trademarks that a firm has registered in the two-year window prior to IPO. *Predicted Ln(1+ No. of Trademarks)* is the predicted value of natural logarithm of one plus the total number of trademarks obtained from the first stage regression. *Ln(Assets)* is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. *Ln(Underwriter Reputation)* is the natural logarithm of the lead underwriter's reputation ranking, obtained from Jay Ritter's website. *Ln(1 + Firm Age)* is the natural logarithm of one plus the number of years from the founding year of a firm to the year of IPO. *Tobin's Q* is the ratio of market and book value of assets computed using the first trading day closing price. *No. of Trademark Applications* is the number of trademark applications made by a firm in the two-year window prior to the IPO. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm between five years prior to the first round of VC investment and the year of IPO. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. Constant, two-digit SIC industry fixed effects, year fixed effects, and state of a firm's headquarters fixed effects are included in all regressions. All standard errors are clustered at the two-digit SIC code industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OIBDA							
Variables	Year 1		Year 2		Year 3		Year 4	
Predicted Ln (1+ No. of Trademarks)	-0.069	-0.054	-0.374	-0.394	0.853*	0.844*	0.559*	0.559
	(0.280)	(0.296)	(0.521)	(0.509)	(0.429)	(0.395)	(0.288)	(0.320)
Ln(Assets)	0.066**	0.065**	0.164**	0.167**	0.087	0.089	0.161**	0.161**
	(0.026)	(0.027)	(0.067)	(0.065)	(0.073)	(0.073)	(0.066)	(0.067)
Ln(Underwriter Reputation)	0.024	0.023	0.040	0.032	-0.061	-0.065	0.152	0.154
	(0.053)	(0.053)	(0.074)	(0.076)	(0.157)	(0.156)	(0.157)	(0.161)
Ln(1 + Firm Age)	0.012	0.012	0.077	0.081	0.005	0.007	-0.019	-0.020
	(0.079)	(0.080)	(0.132)	(0.136)	(0.190)	(0.192)	(0.147)	(0.147)
Tobin's Q	0.003	0.003	0.003	0.002	-0.006	-0.007	0.004*	0.004*
	(0.004)	(0.004)	(0.010)	(0.009)	(0.008)	(0.007)	(0.002)	(0.002)
No. of Trademark Applications	0.000	-0.000	0.004	0.004	-0.027**	-0.027**	-0.018**	-0.019**
	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)	(0.010)	(0.006)	(0.007)
Ln(1 + No. of Patents)	0.017		-0.027		-0.064		0.005	
	(0.015)		(0.022)		(0.045)		(0.052)	
Ln(1 + No. of Citations)		1.144*		0.686		-1.515		0.358
		(0.650)		(1.112)		(1.408)		(1.700)
Observations	303	303	238	238	194	194	166	166
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: The Relation between Trademarks and the Information Asymmetry Facing Firms

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

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Forecast Error		Dispersion		No. of Analysts	
Ln(1+No. of Trademarks)	-0.006	-0.007	-0.098*	-0.098*	0.243*	0.310**
	(0.010)	(0.010)	(0.053)	(0.055)	(0.120)	(0.139)
Ln(Underwriter Reputation)	-0.019	-0.020	-0.118	-0.112	-0.061	-0.024
	(0.016)	(0.016)	(0.089)	(0.083)	(0.223)	(0.217)
Ln(Assets)	-0.003	-0.003	0.016	0.014	1.142***	1.136***
	(0.010)	(0.010)	(0.048)	(0.047)	(0.226)	(0.222)
Ln(1 + Firm Age)	-0.018**	-0.017*	-0.063	-0.060	-0.263	-0.280
	(0.008)	(0.008)	(0.066)	(0.064)	(0.165)	(0.176)
Tobin's Q	-0.003***	-0.003***	0.003	0.003	0.090***	0.092***
	(0.000)	(0.000)	(0.008)	(0.008)	(0.019)	(0.019)
Ln(1 + No. of Patents)	-0.009		0.036		0.462*	
	(0.010)		(0.044)		(0.230)	
Ln(1 + No. of Citations)		0.024		3.519		6.633
		(0.481)		(3.730)		(4.897)
Observations	719	719	629	629	860	860
Adjusted R-squared	0.001	0.0001	0.049	0.052	0.320	0.313
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

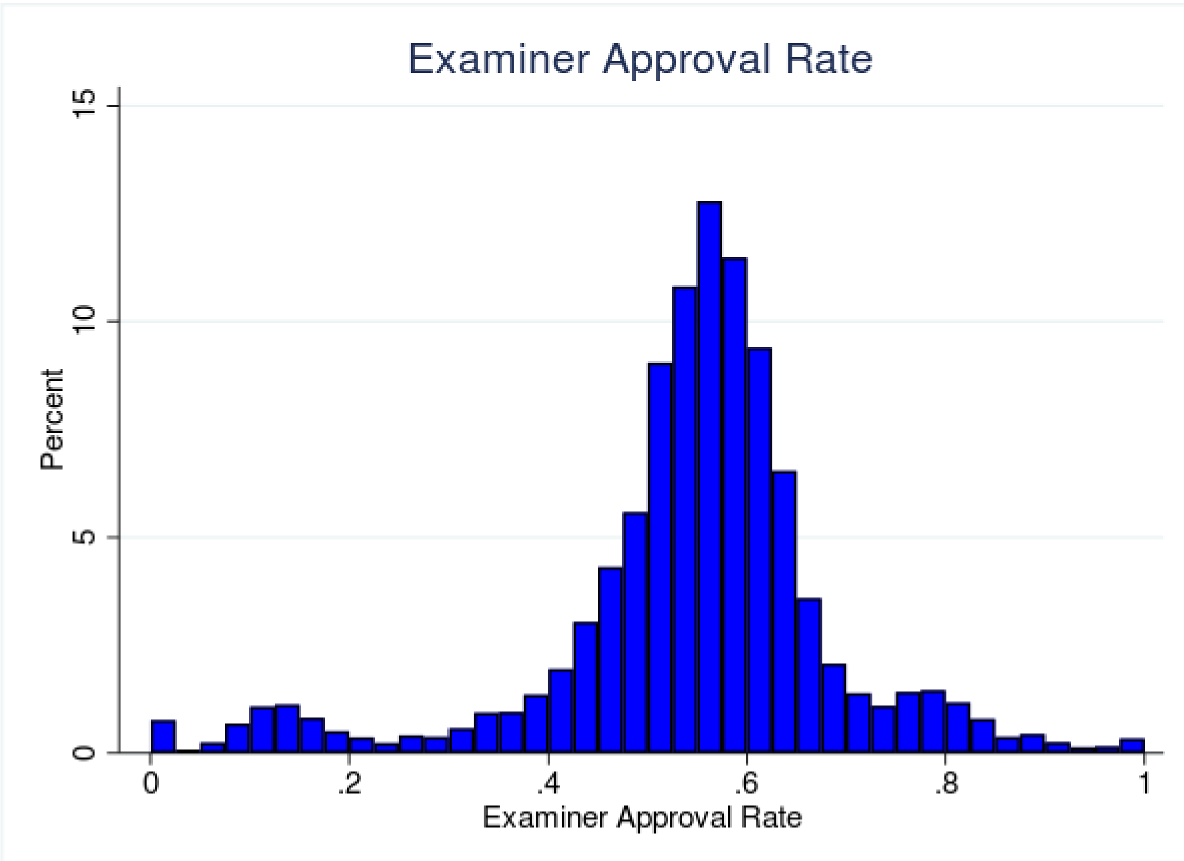
Table 12: Instrumental Variable Analysis of the Relation between Trademarks and Information Asymmetry Facing the Firm

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

		(1)	(2)	(3)	(4)	(5)	(6)
	First Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage
Variables	Ln(1+ No. of Trademarks)	Forecast Error		Dispersion		No. of Analysts	
Examiner Leniency	1.501***						
	(0.254)						
Predicted Ln(1+ No. of Trademarks)		-0.245**	-0.250**	-0.614	-0.423	1.331	1.608
		(0.098)	(0.097)	(0.907)	(0.840)	(1.920)	(1.982)
Ln(Underwriter Reputation)	0.016	-0.021	-0.020	-0.124**	-0.109*	0.034	0.066
	(0.048)	(0.018)	(0.018)	(0.050)	(0.054)	(0.369)	(0.365)
Ln(Assets)	0.068***	0.033**	0.033**	0.102	0.085	1.206***	1.178***
	(0.023)	(0.014)	(0.014)	(0.091)	(0.112)	(0.329)	(0.305)
Ln(1 + Firm Age)	0.059	-0.000	0.001	-0.110	-0.131	-0.542***	-0.552**
	(0.047)	(0.022)	(0.023)	(0.079)	(0.096)	(0.186)	(0.198)
Tobin's Q	0.004	-0.002	-0.002	-0.005	-0.004	0.074**	0.075**
	(0.003)	(0.001)	(0.001)	(0.005)	(0.005)	(0.030)	(0.030)
No. of Trademark Applications	0.028***	0.005**	0.005**	0.014	0.009	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.028)	(0.030)	(0.043)	(0.045)
Ln(1 + No. of Patents)	0.020	0.001		0.056		0.366	
	(0.016)	(0.015)		(0.076)		(0.276)	
Ln(1 + No. of Citations)			0.447		6.085		5.761
			(0.871)		(5.437)		(5.324)
Observations	438	438	438	382	375	530	530
F Statistic from 1st Stage	34.874						
Adjusted R-squared	0.308						
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Distribution of Trademark Examiner Approval Rates

This figure shows the sample distribution of annual trademark examiner approval rates, defined as in equation (1). The sample consists of all trademark applications available at USPTO website from 1982 to 2015. We only consider examiners who have reviewed minimum 10 applications in a year.



Appendix

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

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

$$Examiner\ Leniency_{it} = \alpha_0 + X_{it} + \epsilon_{it}, \tag{1}$$

where *Examiner Leniency* is the average leniency of examiners across all trademark applications filed by the firm i in the prior two year period. X represents a set of firm, investor, or investment characteristics. Our sample consists of all VC-backed private firms filing at least one trademark application in the prior two year period before their exit or failure to exit. We control for firm-specific characteristics: the number of patents (or citations on patents) held by a firm from five years prior to receiving the first round of VC-investment to the year of receiving the first round of VC-investment, and age of the firm at the time of receiving the first round of VC-investment. We also control for investor characteristics: age of the lead VC at the time of receiving the first round of VC investment. Lastly, we control for investment characteristics: total investment made in the firm by all VCs across all rounds and the number of rounds of VC investment (staging). We include fixed effects for industry, year, firm-headquarter state, and lead VC in our regressions and cluster standard errors at the lead VC level. In Table A1, our results show that firm or investor or investment characteristics do not affect examiner leniency. This test provides some support for the notion that our instrument, namely, trademark examiner, leniency is valid.

A.2: Propensity Score Matching Analysis

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

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

We assess the efficacy of our matched sample in Table A2. Panel A shows the comparison between treated and control firms prior to matching. Panel B compares treated and control firms after matching: we find that treated and control firms are similar across all observables after matching. After balancing the sample, we use the propensity score matched subsample to run various regressions. Since in this subsample some control firms are matched with multiple treated firms, we use the weighted least squares (WLS) regressions in which the weight for each treated firm is one, while the weight for each control firm is equal to the number of times it is used as a

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

match for treated firms. We find that all our WLS regression results using the propensity score matched sample are similar to our baseline OLS results documented in the main body of the paper.

A.2.1 Propensity Score Matching Analysis of Trademarks and IPO and Secondary Market Valuation

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and its IPO and immediate secondary market valuations. We report these results in Table A3. In Columns (1) and (2), the dependent variable is IPO valuation. We find that the coefficients of trademarks are positive and significant at the 1 percent level. In Columns (3) and (4), the dependent variable is secondary valuation computed using first day closing price. We find that the coefficients of trademarks are positive and significant at the 5 percent level. Finally, in Columns (5) and (6), we use secondary valuation computed using first post-IPO fiscal quarter price as our dependent variable. The coefficients of trademarks are positive and significant at the 1 percent level. In sum, we find that a larger number of trademarks leads to higher IPO and immediate secondary valuations, supporting our hypotheses **H4** and **H5**.

A.2.2 Propensity Score Matching Analysis of Trademarks and Participation of Institutional Investors in a Firm's IPO

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and participation of institutional investors in its IPO. We report these results in Table A4. In Columns (1) and (2), the dependent variable is the natural logarithm of one plus the number of institutional investors holding shares in the firm, and the coefficients of trademarks are significant at the 1 percent level for both the columns. In sum, we find that a larger number of trademarks lead to greater institutional investor participation in the IPO, supporting our hypothesis **H6**.

A.2.3 Propensity Score Matching Analysis of Trademarks and Post-IPO Operating Performance

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and its post-IPO operating performance. We report these results in Table A5. In Columns (1) and (8), the dependent variables are the operating performance in years 1, 2, 3, and 4 after IPO. We show that firms with higher number of trademarks are associated with higher level of post-IPO operating performance. The results are significant at 1 percent levels in Columns (1), (2), (3), (4), (7), and (8). Broadly, our results show that a larger number of trademarks lead to a higher level of post-IPO operating performance, consistent with our hypothesis **H7**.

A.2.4 Propensity Score Matching Analysis of Trademarks and the Information Asymmetry Facing the Firm in the Post-IPO Market

In this section, we present the results of our propensity score matching analysis of the relation between the number of trademarks registered by a firm at IPO and the extent of information asymmetry facing the firm in the post-IPO equity market. We report these results in Table A6. In Columns (1) and (2), the dependent variable is analyst forecast error, and we find that the coefficients of trademarks are negative but insignificant. In Columns (3) and (4), the dependent variable is analyst forecast dispersion, and the coefficients of trademarks are negative as expected and significant at the 10 percent level. In Columns (5) and (6), the dependent variable is the number of analysts covering the firm, and the coefficients of trademarks are significant at the 10 percent level. In sum, we show that a larger number of trademarks lead to a lower extent of information asymmetry facing the firm in the equity market, which lends support for our hypothesis **H8**.

A.3 The Relation between Trademarks and Propensity for Successful Exit

We study the relation between the number of trademarks and successful exits of VC-backed private firms, corresponding to our hypothesis **H3**, by estimating a probit model. We have the same set of controls as our baseline linear probability regressions. We present the results of the above regressions in the Table A7. In Columns (1) and (2), we use IPO and acquisition dummy as the dependent variable. We find that the coefficients of trademarks are positive and significant at the 1 percent level. In Columns (3) and (4), we use the IPO dummy as the dependent variable. We find that the coefficients of trademarks are positive and significant (at the 5 percent and 1 percent level, respectively). Finally, in Columns (5) and (6), we use the acquisition dummy and find that the coefficients of trademarks are positive and significant at the 1 percent level. These results suggest that firms with a larger number of trademarks are associated with a greater chance of successful exit, which supports our hypothesis **H3**.

Next, we run a two-stage probit regression model and use measures of successful exits as the dependent variable in the second stage. We include the same controls and dummy variables as in our corresponding baseline linear regressions. We also include an additional control, i.e., the number of applications ($Applications_{it}$) in both stages, to control for the fact that a firm with more applications may be likely to have more registered trademarks. We report the results of these regressions in Table A8. In Column (1), we report the first-stage regression result of our IV analysis, which corresponds to successful exit through IPO or acquisitions (corresponding second stages shown in Columns (2) and (3)). We find that the coefficient of our instrument (*Examiner Leniency*) is positive and significant at the 1 percent level. The first-stage F-statistic is 29.60 and the adjusted R-squared is 25.7 percent, suggesting that our instrument satisfies the relevance condition for a valid instrument. Corresponding first stage results for other two measures of successful exit (IPO only and M&A only) satisfy the relevance condition, but are suppressed in the table. We report the second-stage regression results in Columns (2) to (7). In Columns (2) and (3), the dependent variable is a dummy variable for IPOs and acquisitions (*IPO and M&A*). We find that the coefficients of the trademark measure are positive and significant at the 1 percent level. In Columns (4) and (5), the dependent variable is a dummy variable for IPOs (*IPO only*). The coefficients of the trademark measure are positive but insignificant. Finally, in Columns (6) and (7), the dependent variable is a dummy variable for acquisitions (*M&A only*). We find that the coefficients of the trademark measure are positive and significant at the 1 percent level. Thus, our IV analysis results show that the positive relation between trademarks on the likelihood of successful exits of VC-backed private firms is causal. This supports our hypothesis **H3**.

References

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

Table A1: Regression Analysis showing that Trademark Examiner Leniency is Uncorrelated to Firm, Investment, and Investor characteristics

In this table, we report the OLS regression of regressing trademark examiners' leniency on firm, investor, and investment characteristics to show that our instrument, examiners' leniency, is unaffected by these characteristics. Our sample consists of all the trademark applications made by VC-backed private firms in our sample after receiving the first round of investment to their IPO or acquisition in case of an exit or up to five years from receiving the last round of VC investment, defined as *No Exit. Examiner Leniency*, is the examiner leniency averaged over all the trademark applications filed by a firm in the two-year window prior to their exit or *No Exit*. *Ln(1 + No. of Patents)* is the natural logarithm of one plus the total adjusted number of patents filed and eventually granted to a firm in the five-year period before the first round of VC investment. *Ln(1 + No. of Citations)* is the natural logarithm of one plus the total adjusted number of forward citations received by these patents. *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. *Ln(Total Investment)* is the natural logarithm of the total VC investments across all rounds received by a private firm. *Ln(1 + VC Age)* is the natural logarithm of one plus the number of years from the founding year of the lead VC to the year of first round of lead VC investment at the private firm. *No. of Rounds by VCs* is the total number of rounds of VC investments received by a private firm. Constant and dummy variables for two-digit SIC, year, state of a firm's headquarters, and Lead VC are included in all regressions. All standard errors are clustered at the Lead VC level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

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

Table A2: Propensity Score Matching Diagnostic Tests

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

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

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

Table A3: Propensity Score Matching Analysis of the Relation between Trademarks and IPO and Immediate Secondary Market Valuations

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

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	IPO Valuation		Secondary Valuation (FD)		Secondary Valuation (FQ)	
Ln(1 + No. of Trademarks)	0.378***	0.386***	0.422**	0.436**	0.678***	0.691***
	(0.091)	(0.089)	(0.175)	(0.166)	(0.202)	(0.203)
Ln(Underwriter Reputation)	-0.056	-0.053	-0.191	-0.195	-0.441	-0.398
	(0.140)	(0.147)	(0.200)	(0.176)	(0.269)	(0.260)
Ln(Assets)	-0.460***	-0.461***	-1.013***	-1.016***	-1.020***	-1.016***
	(0.098)	(0.100)	(0.243)	(0.242)	(0.255)	(0.260)
Ln(IPO Proceeds)	0.515***	0.525***	2.539***	2.557***	2.329***	2.336***
	(0.182)	(0.175)	(0.518)	(0.517)	(0.516)	(0.528)
Ln(1 + Firm Age)	0.209	0.203	-0.203	-0.214	-0.605**	-0.634**
	(0.185)	(0.177)	(0.217)	(0.199)	(0.243)	(0.249)
ROA	-1.748**	-1.780**	-1.883	-1.935	-1.498	-1.569
	(0.807)	(0.835)	(1.166)	(1.199)	(1.213)	(1.266)
Ln(1 + No. of Patents)	0.073		0.096		0.358	
	(0.098)		(0.319)		(0.291)	
Ln(1 + No. of Citations)		-1.656		-5.194		4.644
		(4.665)		(5.528)		(8.434)
Observations	967	967	997	997	1,048	1,048
Adjusted R-squared	0.136	0.136	0.226	0.226	0.235	0.234
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A4: Propensity Score Matching Analysis of the Relation between Trademarks and the Participation of Institutional Investors in a Firm's IPO

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

Variables	(1)	(2)
	Ln(1 + No. of Institutional Investors)	
Ln(1 + No. of Trademarks)	0.095***	0.091***
	(0.032)	(0.032)
Ln(Underwriter Reputation)	0.059	0.054
	(0.061)	(0.064)
Ln(Assets)	0.022	0.023
	(0.032)	(0.030)
Ln(IPO proceeds)	0.583***	0.586***
	(0.064)	(0.067)
Ln(1 + Firm Age)	-0.091*	-0.086
	(0.049)	(0.053)
Underpricing	0.261***	0.257***
	(0.031)	(0.030)
Tobin's Q	-0.014***	-0.014***
	(0.004)	(0.004)
Ln(1 + No. of Patents)	-0.075**	
	(0.036)	
Ln(1 + No. of Citations)		-1.493*
		(0.748)
Observations	801	801
Adjusted R-squared	0.572	0.569
Industry FE	Yes	Yes
Year FE	Yes	Yes
State FE	Yes	Yes

Table A5: Propensity Score Matching Analysis of the Relation between Trademarks and Post-IPO Operating Performance

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OIBDA							
Variables	Year 1		Year 2		Year 3		Year 4	
Ln(1 + No. of Trademarks)	0.055***	0.056***	0.073***	0.069***	0.065	0.085	0.097***	0.087***
	(0.018)	(0.017)	(0.021)	(0.021)	(0.068)	(0.071)	(0.026)	(0.027)
Ln(Assets)	0.075***	0.075***	0.066***	0.063***	0.124*	0.132*	0.055***	0.055***
	(0.018)	(0.018)	(0.011)	(0.011)	(0.066)	(0.068)	(0.013)	(0.014)
Ln(1 + Firm Age)	0.019	0.018	0.071	0.094*	0.415***	0.382**	-0.007	0.038
	(0.039)	(0.040)	(0.042)	(0.052)	(0.142)	(0.141)	(0.039)	(0.039)
Ln(Underwriter Reputation)	0.048**	0.050**	0.011	0.006	-0.062	-0.052	0.033	0.020
	(0.022)	(0.024)	(0.033)	(0.035)	(0.070)	(0.068)	(0.039)	(0.037)
Tobin's Q	0.003	0.003	0.006*	0.005	0.038***	0.040***	0.004***	0.003***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.008)	(0.010)	(0.001)	(0.001)
Ln(1 + No. of Patents)	0.015		-0.061**		0.156**		-0.071**	
	(0.026)		(0.027)		(0.065)		(0.026)	
Ln(1 + No. of Citations)		0.376		0.178		3.476		-0.919
		(0.993)		(0.765)		(3.753)		(1.868)
Observations	604	604	479	479	403	403	325	325
Adjusted R-squared	0.478	0.478	0.385	0.375	0.248	0.244	0.459	0.445
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Propensity Score Matching Analysis of the Relation between Trademarks and the Information Asymmetry Facing the Firm

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

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Forecast Error		Dispersion		No. of Analysts	
Ln(1 + No. of Trademarks)	-0.001	-0.002	-0.120*	-0.123*	0.343*	0.358*
	(0.012)	(0.011)	(0.062)	(0.064)	(0.183)	(0.192)
Ln(Underwriter Reputation)	-0.007	-0.008	-0.047	-0.045	-0.035	0.005
	(0.020)	(0.020)	(0.098)	(0.098)	(0.202)	(0.210)
Ln(Assets)	-0.008*	-0.008*	-0.053	-0.054	1.061***	1.054***
	(0.005)	(0.004)	(0.067)	(0.067)	(0.269)	(0.264)
Ln(1 + Firm Age)	-0.010	-0.009	-0.086	-0.083	-0.267	-0.278
	(0.007)	(0.007)	(0.112)	(0.113)	(0.204)	(0.206)
Tobin's Q	-0.003***	-0.003***	0.002	0.002	0.092***	0.094***
	(0.001)	(0.001)	(0.007)	(0.007)	(0.022)	(0.021)
Ln(1 + No. of Patents)	-0.015		-0.023		0.328*	
	(0.009)		(0.032)		(0.179)	
Ln(1 + No. of Citations)		-0.251		0.674		8.371*
		(0.339)		(1.445)		(4.138)
Observations	854	854	755	755	1,003	1,003
Adjusted R-squared	0.053	0.051	0.235	0.235	0.362	0.359
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: The Relation between Trademarks and the Propensity for Successful Exit

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

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

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

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

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage	Second Stage
	Ln (1+ No. of Trademarks)	IPO and M&A	IPO and M&A	IPO only	IPO only	M&A only	M&A only
Examiner Leniency	0.739***						
	(0.129)						
Predicted Ln (1+ No. of Trademarks)		1.628***	1.625***	0.164	0.238	1.371***	1.363***
		(0.168)	(0.169)	(0.866)	(0.852)	(0.267)	(0.265)
Ln(1 + Firm Age)	0.062***	-0.163***	-0.169***	0.054	0.063	-0.158***	-0.167***
	(0.020)	(0.058)	(0.058)	(0.085)	(0.085)	(0.053)	(0.052)
Ln(Total Investment)	-0.017	0.123***	0.113***	0.256***	0.274***	0.040	0.024
	(0.014)	(0.040)	(0.040)	(0.053)	(0.053)	(0.032)	(0.032)
Ln(1 + VC Age)	0.028	-0.312	-0.303	-0.083	-0.090	-0.307**	-0.301*
	(0.060)	(0.211)	(0.212)	(0.258)	(0.256)	(0.153)	(0.154)
Ln(VC Fund Size)	0.112***	-1.153***	-1.165***	-0.574***	-0.542***	-0.245***	-0.268***
	(0.024)	(0.246)	(0.245)	(0.113)	(0.112)	(0.061)	(0.061)
No. of Rounds by VCs	-0.008	0.039**	0.038**	0.032	0.036*	0.003	-0.000
	(0.006)	(0.018)	(0.018)	(0.020)	(0.020)	(0.014)	(0.014)
Average No. of VCs per Round	0.001	0.015	0.014	0.069**	0.068**	-0.036	-0.036
	(0.009)	(0.028)	(0.028)	(0.031)	(0.031)	(0.024)	(0.024)
No. of Trademark Applications	0.036***	-0.052***	-0.053***	0.017	0.016	-0.059***	-0.060***
	(0.005)	(0.011)	(0.011)	(0.030)	(0.030)	(0.010)	(0.010)
Ln(1 + No. of Patents)	0.008	-0.071		0.231***		-0.167***	
	(0.017)	(0.053)		(0.063)		(0.053)	
Ln(1 + No. of Citations)			0.935		3.082		-1.262
			(2.240)		(2.331)		(1.908)
Observations	2,214	2,214	2,214	2,129	2,129	2,480	2,480
F Statistic from 1st Stage	29.60						
Adjusted R-squared	0.257						
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 3

How does Online Employee Ratings Affect External Firm Financing? Evidence from Glassdoor

3.1 Introduction

It has long been well known that the information environment of a firm affects its corporate financial policies: see, Myers and Majluf (1984), who analyze the effect of private information on the equity issue decisions of firms and develop a pecking order theory of firm's choice among financial instruments to raise external financing (see also Giammarino and Lewis (1988)). However, in recent years there has been significant changes in the information environment facing firms. In particular, the explosive growth in computing power in recent years, and the reduction in the costs of disseminating economically relevant information due to the widespread use of the internet has significantly enhanced the ability of investors to produce and transmit information useful for valuing firms' equity and for evaluating firm's financing and investment policies. Employees are an important source of production and dissemination of useful information. To give one example, there have been several internet sites that allow employees to rate a firm's management, its work culture, its compensation schemes, as well as its overall future prospects, e.g., Glassdoor Employee Ratings. While it is difficult to argue that such ratings directly reduce the information asymmetry facing firms in the equity market (since the employees giving the ratings involved may not be senior officers of these firms), such ratings may be taken into account by equity market investors when valuing firms' equity. However, there has been no empirical analysis in the literature so far analyzing how information provided by employees on a public platform affect the external financing and investment policies of firms. The objective of this paper is to fill this gap in the literature by analyzing the effect of online employee ratings of firms available with investors on firms' external financing and investment policies.

We view online employee ratings as soft information available to equity market investors (over and above any publicly available information available to them about the firm) which they can use to value a firm's equity and evaluate its financing policies such as its decision whether or not to issue equity to finance its projects; its choice of external financing between equity and debt; and its investment policy.[1] We make use of a large sample of around 1.1 million employee ratings from the Glassdoor website covering a sample of 2842 public firms during the period 2008 to 2017 to construct our proxy for information provided by employees. We analyze the impact of employee ratings on the external financing policies of firms, their stock returns upon equity issue announcements, their propensity to have a positive stock return upon an equity issue announcement, their choice between issuing debt and equity, their investment policies, the participation of institutional investors in their seasoned equity issues, and their post-issue operating performance.

The theoretical framework we use to develop our testable hypotheses is based on the model of Chemmanur and Jiao (2005), who introduce soft information into a three-type setting with insider private information similar to that of Myers and Majluf (1984). Chemmanur and Jiao (2005) show that, when investors may rely on soft information in addition to observing the equity issue or no-issue decision announced by firm insiders, the inverse monotonic relation between firm type and equity issuance (as in Myers and Majluf (1984)) disappears: i.e., it is no longer the case that the lower type firms prefer to issue equity while the higher type firms do not. Thus, in the Chemmanur and Jiao (2005) setting, with three firm types, namely, type G (Good), type M (Medium), and type B (Bad) firms, the good and bad type firms issue equity while the medium type firm prefers not to issue equity and to pass up investment in its positive net present value project (i.e., the type M firm underinvests). The intuition here is that, in the presence of soft information, the highest type (type G) firm chooses to issue equity since it expects to rely on the realization of soft information (arriving at the time of the equity issue) to reduce any undervaluation of its equity coming from pooling with the lowest type (type B) firm (which also attempts to issue equity at a similar price). Such a reduction in undervaluation arising from soft-information may not be substantial enough for the medium type (type M) firm to issue equity, since its soft information realization can be expected to be closer to that of a bad (type B) firm, so that investors may not be able to rely on such information to distinguish between the medium type and bad type firms. The above loss

[1] Online employee reviews contain information that is not in traditional sources of hard information, such as financial statements. As the excellent review article by Liberti and Petersen (2018) points out, there is no clear dichotomy between hard and soft information, and we should think of a continuum along which information can be classified. In our setting, we can think of soft information as noisy information correlated with intrinsic firm value and performance, but on which it is difficult to write legally enforceable contracts.

of the inverse monotonicity in the relation between equity issuance and firm type means that the announcement effect of an equity issue may not always be negative when soft information is present. In particular, Chemmanur and Jiao (2005) show that the announcement effect of an equity issue may be positive or negative in a setting where soft information is available to outside investors in the equity market (depending on the precision of the soft information available to them and the magnitude of the net present value of the firm's project).

We make use of the above theoretical framework (with some additional assumptions) to develop testable hypotheses on the relation between the realizations of the online employee ratings of a firm (prior to an equity issue) and the following: the algebraic value of the abnormal stock return upon the announcement of its equity issue (i.e., the announcement effect); the propensity of the above announcement return to be positive; the propensity of the firm to issue equity rather than debt; firm investment; institutional investor participation in the firm's equity issue; and its long-term post-SEO operating performance. The arrival of internet and social media allows investors to have access to an explosive amount of novel information about many aspects of firms. Online employee ratings are an important example of information available to investors, which, in turn, may affect firms' external financing and investment policies.

We use the following four employee ratings available on the Glassdoor website to construct the main independent variables for our empirical analyses: overall rating, management rating, compensation rating, and cultural rating. All these rating variables are correlated and capture different aspects of online employee ratings. Since our focus is on capturing information contained in employee reviews and given that different employee rating measures capture different pieces of information, we also use common factor analysis to create a "rating factor" that captures the information content common to all the above different rating measures. We use these measures (the four rating available directly from the Glassdoor website and the rating factor we construct) to test the impact of online employee ratings on the external financing and investment policies of firms.

We now summarize the results of our empirical analysis. First, we show that firms with higher average online employee ratings prior to equity issues are associated with an algebraically greater abnormal stock returns upon announcement of an equity issue (3-day cumulative abnormal stock return (CAR)), i.e., with higher announcement effects. Our results are also economically significant:

a one standard deviation increase in overall rating is associated with a 1.7 percentage point increase in the abnormal stock return. This is substantial as the CAR for a median firm is -2 percent. Second, we show that firms with higher average online employee ratings are associated with a greater propensity to have *positive* announcement effects.[2] Again, the above results are economically significant. A one standard deviation increase in overall rating is associated with a 6.7 percentage point increase in the probability of a firm having a positive announcement effect. This is equivalent to an increase of 19.2 percentage in the average firm's probability of having a positive announcement effect.

Third, we show that firms with higher prior average online employee rating realizations are associated with a greater propensity to issue equity rather than debt to raise external financing. A one standard deviation increase in overall rating is associated with a 1.6 percentage point increase in the probability of issuing equity over debt. This is equivalent to an increase of 5.5 percent in the average firm's probability of issuing equity rather than debt. Fourth, we show that firms with higher prior average online employee rating realizations are associated with a greater level of annual investment expenditures. A one standard deviation increase in overall rating is associated with an increase of 6 percentage point in annual investment expenditures made by a firm. This is equivalent to an increase of 11.3 percent in the average firm's annual investment expenditure.

Fifth, we show that firms with higher prior average online employee rating realizations are associated with greater participation by institutional investors in their SEOs. A one standard deviation increase in overall rating is associated with an increase of 10 institutional investors investing in the firm's SEO. This is equivalent to a 10 percent increase in institutional investor participation for the median firm. Sixth, we show that firms with higher prior average online employee rating realizations are associated with better long-run post-SEO operating performance. A one standard deviation increase in the common factor rating is associated with an increase of 6.2 percentage point in the operating performance of a firm over the three years subsequent to the SEO.

Our baseline (OLS) analyses may suffer from some endogeneity concerns. It may be possible that higher quality firms have higher announcement returns and have higher online employee ratings. Further, such firms may have greater probability of positive announcement returns and may have

[2] It has been documented that firms with SEOs have negative announcement effects on average. In our sample, only 35 percent of firms have positive announcement effects.

cheaper access to external financing from the equity market. In other words, it may be argued that our baseline analysis results reflect only the correlation between online employee ratings and intrinsic firm value, rather than online ratings changing the underlying information environment (and causing firms to have algebraically higher SEO announcement effects; greater probability of a positive SEO announcement effect; and most important, causing them to change their external financing policies in favor of issuing equity rather than debt).

To address the above endogeneity concern, we make use of the staggered adoption of Anti-SLAPP laws, which protect the First Amendment Rights of U.S. citizens, across the U.S. states. SLAPP (strategic lawsuit against public participation) is a retaliatory lawsuit filed against an opponent or critic who has spoken against the plaintiff on a public forum. SLAPP lawsuits are filed against online reviewers as well.[3] SLAPP lawsuits may have chilling effects on online reviewers due to the threat of litigation and may reduce the information content of those reviews. The provision of anti-SLAPP laws in some states may therefore potentially affect the propensity of individuals to provide online reviews (and ratings) of firms and to provide more informative reviews. This is because anti-SLAPP laws provide provisions for recovery of attorney fees of defendants, swift dismissal of meritless lawsuits, and puts the burden on plaintiffs to prove the merits of their cases.

We make use of the staggered adoption (and in some cases rejection) of anti-SLAPP laws in U.S. states using a difference-in-differences (DID) approach. We provide empirical evidence which show that the passage of anti-SLAPP laws across states leads to greater no of reviews of firms on Glassdoor, i.e., greater participation by reviewers. We also show that the passage of anti-SLAPP laws also leads to lower Glassdoor ratings, which suggests that anti-SLAPP laws may encourage employees with negative views on their firms to express their opinion. We use a propensity score matching analysis to create a matched sample of firms headquartered in states with and without anti-SLAPP laws. We do this matching to ensure that treated and control groups are similar in terms of observables.[4] Next, we conduct a DID analysis on the above matched sample. We expect the online employee ratings to have greater information content after the passage of anti-SLAPP laws. Anonymous reviewers for such firms will be less affected by threats of litigation

[3] Please refer this link for an example of lawsuit filed against reviewers on the Glassdoor website: https://www.glassdoor.com/blog/glassdoor-protect-anonymous-free-speech/.

[4] Our results are robust to conducting our DID analysis over the entire unmatched sample as we show in our appendix.

(e.g., defamation lawsuits) compared to reviewers for firms headquartered in states with no anti-SLAPP laws. Additionally, Glassdoor reviewers are likely to be aware of anti-SLAPP laws since Glassdoor mentions the laws on its website and that, in some cases, it files anti-SLAPP motions on behalf of its anonymous reviewers to protect their identity. Hence, outside investors may put greater weight on the information contained in online employee ratings for firms headquartered in states with prevailing anti-SLAPP laws. The passage of anti-SLAPP laws are clearly exogenous to the issuance of equity by firms so that these laws provide an appropriate economic setting for our identification tests. We also show empirically that local economic or political factors in states do not determine the passage of anti-SLAPP laws.

Our DID analysis shows that external financing and investment level of firms are affected by the staggered passage of anti-SLAPP laws across states. We find that the passage of anti-SLAPP laws leads to greater announcement effects; a greater probability of a positive announcement effect; a greater probability of issuing equity rather than debt; and greater level of post-SEO investment for firms. Note that, in conducting the above analysis, we are careful to address some common concerns associated with the DID approach. In our empirical specification, we ensure that treated and control groups are similar on observable covariates (due to matching). Further, we conduct a time-trend analysis to ensure that there is no reverse causality and that our results satisfy the parallel trends assumption. Our results show that there is no trend in the announcement effect prior to the implementation of anti-SLAPP laws in various states. We also provide cross-sectional evidence which shows that the impact of Glassdoor ratings are stronger after the passage of anti-SLAPP laws across U.S. states. Lastly, we also provide empirical evidence that rules out manipulation of Glassdoor ratings of firms prior to their equity issues.

The rest of the paper is organized as follows. Section 2 discusses the relation of our paper to the existing literature. Section 3 describes a theoretical framework for incorporating soft information into an asymmetric information setting and develops testable hypotheses using the above framework (along with some additional assumptions). Section 4 describes our data and sample selection procedures. Section 5 presents our baseline empirical tests and results. Section 6 describes our identification strategy and the corresponding empirical results. Section 7 concludes.

3.2 Relation to the Existing Literature and Contribution

Our paper contributes to several strands in the literature. The first strand is the theoretical literature on SEOs. On the theoretical side, Myers and Majluf (1984) have developed a model with information asymmetry between firm insiders and outside investors to explain the negative stock returns accruing to firms upon an equity issue announcement. Chemmanur and Jiao (2005) theoretically analyze the effect of introducing soft information into the above setting. Their paper is primarily a theoretical paper with some univariate and multivariate analyses studying the correlation between announcement effect and revisions in analyst recommendations and earnings forecasts. In contrast, our paper is an empirical study that shows the causal effect of online employee ratings on external financing and investment policies of firms. Chemmanur and Fulghieri (1999) and Subrahmanyam and Titman (1999) analyze the effects of information production by outsiders (under different assumptions about insider private information and outsiders' cost of producing information) and develop implications for firms' choice between private and public equity financing and for firm investment levels. Our paper contributes to this literature by empirically analyzing how the availability of information provided by employee with equity market investors affects the equilibrium in the equity market and firms' choices between debt and equity issues to raise external finance.[5]

On the empirical front, a number of papers have documented that equity issues are characterized by a negative announcement effect on average: see, e.g., Asquith and Mullins (1986) and Masulis and Korwar (1986). Mikkelson and Parch (1986) document that about one-fourth of their sample firms have a positive announcement effect to equity issue announcements. Loughran and Ritter (1995) show that firms issuing equity underperform in terms of stock returns. Analyzing analyst coverage of firms, Chang, Dasgupta, and Hilary (2006) show that firms facing lower information asymmetry in the equity market are more likely to use equity rather than debt. Gibson, Safieddine, and Sonti (2004) show that institutional investors are able to identify high quality firms and increase their shareholdings in these firms around the offer date. Chemmanur, He, and Hu (2009) show that institutional investors possess private information about SEOs and obtain greater share allocations

[5]To the extent that we analyze the external financing choices of firms between equity and debt issues in the presence of soft information about intrinsic firm value available to outside investors, our paper is also related to the broader theoretical and empirical literature on capital structure: see, e.g., Titman (1984) or Titman and Wessels (1988). See Harris and Raviv (1991) for an excellent review of the theoretical literature on capital structure.

in SEOs which perform better in terms of future long-run stock returns. Gao and Ritter (2010) show that firms choose fully marketed (in the form of road shows by investment banks) SEOs to increase the short-run elasticity of demand for their stocks. Loughran and Ritter (1997) show that the operating performance of firms conducting SEOs improve substantially prior to the equity issue, and then deteriorates after the issue. We contribute to the above empirical literature by analyzing, for the first time the analysing the causal effect of the online employee ratings on the external financing behavior of firms.

We also contribute to the literature studying the role of labor in firms' external financing policies. These papers study the relation between labor and capital structure either through the lens of employee risks (Titman (1984); Berk, Stanton, and Zechner (2010); Agrawal and Matsa (2012); Chemmanur, Cheng, and Zhang (2013); Simintzi, Vig, and Volpin (2015)); and Serfling (2016)) or through the lens of strategic use of debt to bargain with employees (Matsa (2010) and Perotti and Spier (1993)). In contrast to the above papers, we are the first paper in the literate to analyze the causal impact of information provided by employees on their firms' external financial policies .

The next strand of literature related to our paper is the one on information produced by large groups of outsiders (consumers, employees, investors, and others) and its impact on firm outcomes.[6] However, most of these studies analyze the impact of outsiders' information on stock returns. Kelley and Tetlock (2013) show that retail investors predict stock returns.[7] Other studies have analyzed the impact of social media on stock returns (Antweiler and Frank (2004) and Chen, De, Hu, and Hwang (2014)). Several papers have shown that consumer satisfaction also predicts future stock returns (Fornell, Moregson, and Hult (2016) and Huang (2018)). Recently, some papers have studied the impact of employee satisfaction on firm outcomes. Edmans (2011) shows that employee satisfaction is positively correlated with stock returns. Huang, Li, Meschke, and Guthrie (2013) show that employee satisfaction predict firm performance as measured by Tobins'q and return on assets (ROA). Using employee reviews, Sheng (2019) shows that employees' reviews about their firms' business prospects predict future stock returns, and that higher-level employees' reviews are

[6] Most rank and file employees can be regarded as outsiders when it comes to their involvement in decision making in firms.

[7] There is also a large literature on the impact of media on stock returns (Tetlock (2007), Fang and Peress (2009), Solomon (2012), and Gurun and Butler (2012)).

better at predicting future stock returns. Green, Huang, Wen, and Zhou (2019) show that employee rating changes are associated with stock returns. In contrast to the above literature, where the focus is on the asset pricing and market efficiency implications of consumer or other rating, the focus of our paper is on analyzing how the availability of soft information with investors causally affects the financing and investment decisions of firms, which is a first order question in the corporate finance literature.

3.3 Theoretical Framework and Testable Hypotheses

3.3.1 Theoretical Framework

In this section, we briefly outline the theoretical setting for our empirical analysis and develop testable hypotheses. The economic setting we postulate is a three type version of the well-known Myers and Majluf (1984) model with one important difference: investors have available to them a soft information signal which gives them some additional information about the true firm type (intrinsic firm value) over and above the issue/no issue decision. We define a soft information signal here as a signal correlated with firm value, which may be noisy, and which cannot be contracted upon. Such a setting has been analyzed theoretically by Chemmanur and Jiao (2005), and we rely partially on their model to develop testable hypotheses here.

Consider a setting where, at time 0, the risk-neutral insiders of a firm, having private information about its intrinsic value, are deciding whether or not to issue equity to fund their positive net present value project. There are three types of firms: Good (type G) with intrinsic value V_G; Medium (type M) with intrinsic value V_M; and Bad (type B) with intrinsic value V_B; $V_G > V_M > V_B$. While firm insiders know the true type of their own firm, outsiders know only the probability distribution across firm types: they assess that any firm in the equity market is a type G firm with probability ${}_G$, type M firm with probability ${}_M$, and type B firm with probability ${}_B$, with ${}_G + {}_M + {}_B$=*1*. Since outsiders cannot fully distinguish between the three types of firms, the share price of any firm prior to the equity issue announcement will be the pooling value across the three types of firms, i.e, it will be ${}_G\ V_G + {}_M\ V_M + {}_B\ V_B$.

A risk neutral entrepreneur owns the all-equity firm at time -1 (at the date prior to time 0). The firm decides to issue equity or not at time 0. The firm has available to it two economic resources that can generate cash flows in the long-run (at time +1): a new project with a positive net present value (NPV), and assets-in-place. The net present value of the firm's new project is denoted by d, and the investment needed to implement it is denoted by K. The firm has no financial slack to contribute to the new project. Therefore, if the firm chooses to implement the new project at time 0, its managers need to raise the amount K by external financing, and in doing so, it will incur an underwriting fee of c. While we assume initially that the firm can raise only external financing by issuing equity, this assumption will be relaxed later. After implementing the project, the firm will generate a total cash flow of $(K+d)$ in the long-run (at time +1). If the firm chooses not to implement the new project at time 0, the investment opportunity vanishes, and its net present value is extinguished. Although all firms are homogeneous in terms of their investment opportunities, they differ in the value of their assets-in-place (which determines firm type, as discussed earlier). At time +1, the assets-in-place of type G firms generate a cash flow of g, while those of type M and type B firms generate cash flows of m and b, respectively; $g > m > b$. We first briefly describe a "benchmark equilibrium" without soft information.

Benchmark Equilibrium without Soft Information (Myers and Majluf (1984))

(i) *When there is no soft information, there exists an equilibrium in which the type B firm issues equity and invests in the firm's new project, while the type G and type M firms do not issue any equity and do not implement the firm's positive net present value project.*

(ii) *In this equilibrium, the announcement effect of an equity issue will always be negative.*

The benchmark equilibrium above is similar to a discrete (three) type version of the equilibrium in Myers and Majluf (1984), but simplified to its essential element in the sense that, unlike in Myers and Majluf (1984), firm insiders have private information only about their firm's assets in place (and not about the NPV of its new project). Similar to the equilibrium in Myers and Majluf (1984), the higher type firms (type G and type M) choose not to issue equity if the loss in value to their current shareholders arising from selling undervalued equity is greater than the value gain to their current shareholders from implementing their firm's positive net present value project.

On the other hand, the type B firm does not face any such trade-off, since its equity will be priced correctly in equilibrium, so that the value gain to current shareholders from issuing equity and implementing its positive NPV project always dominates. Further, similar to Myers and Majluf

(1984), the announcement effect of an equity issue in this benchmark equilibrium will always be negative. Since the nature of the equilibrium is common knowledge, equity market investors will infer from a firm's announcement of an equity issue that it is a type B firm and will revise the value of its equity accordingly. Since the price of the firm's equity prior to the announcement will be the pooling value across the three firm types, the above revisions will always be downward, resulting in a negative announcement effect always for an equity issue in this benchmark equilibrium.

Equilibrium with Soft Information (Chemmanur and Jiao (2005))

We now introduce soft information into the above three type setting with asymmetric information following Chemmanur and Jiao (2005). By soft information here, we mean a noisy information signal that arrives after the announcement of the equity issue, which outsiders may take into account when deciding whether or not to invest in the firm's equity issue. This soft information has two possible realizations, either "good" (e=H) or "bad" (e=L). Investors receive a good signal with probability $_{\mathrm{i}}$, with a bad signal received with the complementary probability (1-$_{\mathrm{i}}$), i $\in G, M, B$:

$$Pr(e = H|i = G) = \beta_{\mathrm{G}}, Pr(e = H|i = M) = \beta_{\mathrm{M}}, Pr(e = H|i = B) = \beta_{\mathrm{B}}, \tag{3.1}$$

$$\beta_{\mathrm{G}} > \beta_{\mathrm{M}} > \beta_{\mathrm{B}}, \tag{3.2}$$

$$\beta_{\mathrm{G}}, \beta_{\mathrm{M}}, \beta_{\mathrm{B}} < 1. \tag{3.3}$$

Only outside investors observe the realization of their soft information signals: firm insiders observe only the probability distribution of the realization of outsiders' soft information signals, conditional on the type of their own firm.

Assumptions (2) and (3) imply that, while outsiders' soft information signals are informative, they are also noisy.[8] They are informative in the sense that they are positively correlated with the true type of the firm, since a type G firm has a higher probability of outsiders getting good realizations of their soft information signals than a type M firm; similarly, a type M firm has a higher probability of outsiders getting good realizations of their soft information signals than a

[8]For analytical simplicity, in this theoretical framework, we do not allow heterogeneity across outsiders in the soft information signal that they receive and use when evaluating an equity issue: i.e., all outside investors receive the same noisy signal about a given firm. Corresponding to this, we use the average online employee rating received by a given firm, prior to an equity issue, in our empirical analysis (since, in practice, there will be heterogeneity across investors in the realization of their soft information signals about a given firm).

type B firm. They are noisy in the sense that outsiders cannot tell the true type of any firm with probability 1 purely by observing the realization of these soft information signals. In other words, while the information asymmetry between firm insiders and outside investors is lowered by the existence of soft information signals, they do not completely eliminate this information asymmetry. We now briefly describe the characteristics of the soft information equilibrium in Chemmanur and Jiao (2005).

(i) *When there is sufficiently precise soft information that is available to outside investors when deciding whether or not to buy equity in a firm, there exists an equilibrium with the following features:*

The type G firm issues equity, offering a fraction α_u *of the firm's equity to outsiders in exchange for the investment amount K to implement the new project with probability 1. The type M firm does not issue equity at all and does not implement the firm's new project. The type B firm issues equity, offering a fraction* α_u *of the firm's equity to outsiders with the probability y (thus mimicking the type G firm), and a larger fraction* α_d $(\alpha_d > \alpha_u)$ *to outsiders with the complementary probability (1-y), in exchange for the investment amount K. Outsiders accept an offer of* α_u *by a firm if they receive a good realization of their soft information signals about the firm, and reject it otherwise. They always accept an offer of* α_d *by any firm.*

(ii) *Equity issues of firms about which outsiders receive more favorable realizations of their soft information signals will have algebraically larger announcement effects than firms about which outsiders receive less favorable realizations of their soft information signals.*

(iii) *The announcement effect of an equity issue in a soft information equilibrium may be positive or negative. If the soft information signal available to outsiders is precise enough, and if the NPV of the firm's new project, d, is large enough, the announcement effect of the equity issue will be positive. If the soft information signal is less precise, or the NPV of the new project d is not large enough, the announcement effect will be negative.*

In the above equilibrium, the type G firm always offers the low fraction $_u$ (which translates into a high price for the new equity issued), since its firm insiders are confident that, with a very high probability, outsiders will accept such an offer (since outsiders will receive a good realization of their soft information signals for type G firms with a high probability). This, in turn, implies that the type G firm can implement its new project with a very low degree of dilution in current shareholders' equity holdings. The type B firm, on the other hand, has to pay a price if it mimics the type G firm. This cost arises from the fact that its offer at a high price will be rejected by outsiders very often, thereby resulting in it being unable to implement its positive NPV project. This is because outsiders have a much lower probability of getting good realizations of their soft information signals about a type B than a type G firm, which results in its offer being rejected by outsiders more often. Therefore, a type B firm will mimic the type G firm only with a certain probability, setting a low price and revealing its true type with the remaining probability (offering a higher fraction $_d$ of equity to outsiders in return for capital K).

The type M firm, however, will not issue any equity. Since its probability of outsiders receiving a good realization of their soft information signals is lower than that of a type G firm, it will not find it optimal to make an equity offering at a high price (i.e., by offering fraction $_u$ of firm equity in exchange for the capital K). Recall that outsiders will accept such an equity offering at a high price only if they get a good realization of their soft information signals about the firm (allowing them to break even in expectation from their investment) so that a high-price equity offering from a type M firm will be rejected with a high probability (leading the firm to incur the underwriting fee c without any countervailing benefit). At the same time, the type M will not find it optimal to make an equity offering at a low price (fraction $_d$ in exchange for capital K). Since the intrinsic value of the type M is greater than that of the type B, offering equity at the low price would require it to sell significantly undervalued equity (with the resulting severe dilution in current shareholders' equity holding) so that insiders are better off passing up the firm's positive NPV project rather than making such a low-priced equity offering to fund it.[9]

An interesting aspect of the soft information equilibrium of Chemmanur and Jiao (2005) is that, in their setting, the announcement effect may be positive or negative. Further, the magnitude of the announcement effect will be related to the realization of the firm's soft information signal: the more favorable the soft information signal realization about a given firm, the larger (algebraically) the announcement effect will be. Due to space limitations, we discuss the intuition behind the above two results (parts (ii) and (iii) of the soft information equilibrium presented above) in our

[9]Consistent with the above equilibrium firm behavior, outside investors infer (believe) that a firm making a high priced (fraction $_u$ of equity in exchange for capital K) equity offering is a type G firm with a certain probability and a type B firm with the remaining probability. On the other hand, if the firm makes a low priced equity offering (fraction $_d$ of equity in exchange for capital K), they infer (believe) it to be of type B with probability 1, always accepting an equity offering made at a low price.

appendix (subsection A1).

3.3.2 Testable Hypotheses

We now develop testable hypotheses for our empirical analysis based on the theoretical framework discussed in the previous subsection. There are two important differences between our empirical setting and that in the earlier theoretical setting which is important for our empirical tests. First, unlike in the theoretical setting, where the soft information signal arrives after the announcement of the equity issue, in our empirical setting, Glassdoor ratings are given by employees continuously, before and after the equity issue announcement. Thus, both firm insiders and outside investors observe the past realizations of the Glassdoor rating at the time of an equity issue announcement. However, as long as the past realizations of the Glassdoor ratings are not perfectly correlated with the future realizations of these ratings that potential investors use when deciding whether or not to invest in a firm's equity issue, the main predictions of the soft information equilibrium discussed in section 3.1 will hold. We will take advantage of the fact that the past realizations of Glassdoor ratings of a firm and its management will be (imperfectly) correlated with future ratings at the time of the equity issue when developing our main test variable (proxy). Our proxy for the realization of Glassdoor ratings will thus be the average Glassdoor rating (in various categories) received by a firm over the one year prior to the equity issue. Second, the distribution of true values (intrinsic values) of firms in our empirical setting is clearly a continuous distribution, in contrast to the discrete type model of Chemmanur and Jiao (2005) that we used when we developed the broad theoretical framework underlying our empirical analysis. This in turn, implies that it is not meaningful in our empirical setting to talk about the equity issue behavior of good and bad type firms etc.

Despite the above two differences between the theoretical setting and our empirical setting, two important insights from the theoretical setting translate to our empirical setting. First, unlike in a setting without soft information (e.g., Myers and Majluf (1984)), when there is soft information present at the time of the equity issue, it is no longer the case that, in a setting with asymmetric information, higher intrinsic value firms do not issue equity while lower intrinsic value firms issue equity: in other words, the inverse monotonicity between intrinsic firm value and equity issuance no longer holds in the presence of soft information. Second, since both higher intrinsic value and lower intrinsic value (type) firms may issue equity (while some firm types in the middle do not issue), the announcement effect of an equity issue may be either positive or negative, unlike in a setting without soft information, where the announcement effect is always negative (e.g., in Myers and Majluf (1984)).

Our development of testable hypotheses below will reflect the above two important differences between the theoretical framework discussed in section 3.1 and the setting of our empirical analysis.

The Relation between the Announcement Effect of an Equity Issue and the Realization of Online Employee Ratings

The announcement effect (abnormal stock returns upon announcement) of an equity issue will be positively related (algebraically) to online employee ratings on Glassdoor. This follows from the above theoretical framework which predicts that equity issues with favorable realizations of soft information will have higher announcement effect. In our empirical analysis, we use Glassdoor ratings as a proxy for information provided by employees. In other words, if the announcement effect is negative, it will be less negative for the set of firms with a higher realization of Glassdoor ratings, and if the announcement effect is positive, it will be more positive. This implies a positive relation between the average Glassdoor ratings received by the firm in the year prior to the equity issue, and the announcement effect. This is the first hypothesis that we test here (**H1**).

The Relation between the Probability of a Positive Announcement Effect and the Realization of Online Employee Ratings

As we discussed in section 3.1, unlike existing models of equity issues such as Myers and Majluf (1984), in a soft information equilibrium the announcement effect of an equity issue may be positive or negative. A positive announcement effect occurs in a setting with soft information when the equity market revalues the firm upward upon observing its equity issue announcement. Prior to an equity issue announcement, the equity market values the firm as a probability weighted average of the intrinsic values of different possible firm types (intrinsic firm values) conditional on all the information that is available at that time (including prior Glassdoor rating realizations). Upon observing an equity issue announcement, equity market investors revalue the firm, taking into account their beliefs about the set of firm types that are likely to be making the equity issue announcement. If this revised value upon observing the equity issue announcement is higher than the equity value prior to the announcement, the announcement effect will be positive. If the revised value upon investors observing the equity issue announcement is lower than the equity value prevailing prior to the equity issue announcement, then the announcement effect will be negative.

Thus, applying the above theoretical framework in our setting, we expect that the average Glassdoor ratings in the year before the equity issue, and the announcement effect of an equity issue may be positive or negative. This is because, while the set of firms receiving higher Glassdoor rating realizations is likely to be higher intrinsic value firms (so that the market values will be higher on average after an equity issue announcement), their equity value prior to the equity issue announcement will also be higher (since this equity value will reflect their past Glassdoor rating realizations as well). However, the greater the realization of employee ratings of a given firm, the higher the propensity of the firm's equity issue to have positive announcement effect. This is the second hypothesis that we test here (**H2**)

The Relation between the Propensity to Issue Equity rather than Debt and the Realization of Online Employee Ratings

In the theoretical setting discussed in section 3.1, issuing equity is the only source of external financing, so that, if a firm decides not to raise external financing by issuing equity, it will have to pass up its positive NPV project: i.e., it underinvests. We now relax the above assumption and assume, consistent with practice, that, if a firm chooses not to issue equity, it is able to raise external financing by issuing risky debt (defined as debt with a positive probability of default). Let us further assume, again consistent with practice, that firms incurs a deadweight cost in the event of financial distress, and that the probability of a firm entering financial distress will be increasing in its financial leverage. In such a setting, higher type firms will choose to fund their positive NPV projects by issuing equity rather than debt based on the following trade-off. On the one hand, if they choose to issue equity, they will have to sell undervalued equity, since, even in the presence of soft information, there will be some extent of pooling with lower type firms. On the other hand, if they choose to issue debt to raise external financing to fund their positive NPV projects, it will increase their probability of incurring the deadweight costs of financial distress. In equilibrium, firms will choose to issue equity rather than debt by trading off the above undervaluation cost of issuing equity against the expected distress cost of issuing debt.

Given the above, we now develop testable hypotheses on the relation between a firm's realization of Glassdoor employee ratings and its propensity to issue equity rather than debt. Clearly, assuming Glassdoor ratings are informative about true firm type, higher type (higher intrinsic value) firms are likely to receive higher Glassdoor ratings on average. Given this, investors are likely to value the equity of firms with higher Glassdoor ratings at a higher price, so that firms will price their equity at a higher price in an equity issue. To develop intuition, we can think of these firms on average as corresponding to type G firms in our theoretical framework. Thus, the undervaluation costs of issuing equity will be lower for firms receiving higher Glassdoor ratings.[10] At the other extreme, the lowest type firms (intuitively corresponding to the type B firms in our theoretical framework) will pool with the higher type firm by issuing equity at a high price with some probability, while issuing equity at their true value (lower price) with the remaining probability.[11] Finally, for firms of medium intrinsic value (intuitively corresponding to the type M firms in our theoretical framework), which are likely to receive lower values of Glassdoor ratings on average than type G firms, they will have to price their equity significantly lower than their intrinsic value, so that they choose not to issue equity at all but issue debt instead (since their increased expected deadweight cost of financial distress arising from issuing additional debt will be dominated by the incremental undervaluation cost arising from issuing new equity). In summary, given the correlation between true firm type and Glassdoor employee rating realizations, the relation between a firm's prior Glassdoor employee ratings and the probability of its issuing equity rather than debt will be positive. This is the next hypothesis that we test here (**H3**).

The Relation between the Future Firm Investment Levels and the Realization of Online Employee Ratings

Clearly, assuming that Glassdoor employee ratings are informative about firm type (intrinsic value), firms receiving higher realizations of these employee ratings are more likely to be higher type firms. Making the additional assumption (over and above the assumptions made in section 3.1) that higher

[10]Note that even higher type firms will suffer some undervaluation costs of issuing equity, since lower type firms will mimic them in equilibrium by issuing equity at a higher price with some probability. However, the higher the realization of Glassdoor employee ratings received by a firm, the higher valuation of the firm's equity by investors, so that the undervaluation cost of issuing equity will be decreasing in a firm's Glassdoor rating realizations.

[11]For the lowest type firms issuing equity is a dominant strategy, since they do not suffer any undervaluation cost arising from issuing equity: their equity is either overvalued or correctly valued.

types firms have higher quality new investment opportunities as well (where higher quality projects are defined as those with higher NPVs for any given scale), and assuming decreasing returns to scale, we get the prediction that firms with higher prior Glassdoor ratings realizations will have a larger equilibrium investment scale. Further, following hypotheses **H1** and **H2**, we expect that firms with higher Glassdoor ratings should have lower cost of capital, because of lower cost of issuing equity. This lower cost of (discounting factor) will ensure that some negative NPV projects will become positive NPV. Thus, there will be a positive relation between our proxy for soft information and future firm investment levels. This is the next hypothesis that we test here (**H4**).

The Relation between Institutional Investor Participation in SEOs and the Realization of Online Employee Ratings

Clearly, as we discussed so far, firms with higher realizations of Glassdoor ratings will be viewed as higher intrinsic value firms (on average) by investors before as well as after an equity issue announcement. Assuming that institutional investors choose to participate to a greater extent in the SEOs of firms that they view of as higher intrinsic value firms, we get the testable prediction of a positive relation between Glassdoor employee rating realizations and institutional investor participation in the SEO. This is the next hypothesis that we test here (**H5**).

The Relation between long-run post-SEO Operating Performance and the Realization of Online Employee Ratings

We have assumed that Glassdoor employee ratings are informative about firm type (intrinsic value), i.e, firms receiving higher realizations of these ratings are more likely to be higher type (higher intrinsic value) firms. Since higher intrinsic value will manifest itself in the long run through higher operating performance, we expect a positive relation between Glassdoor employee ratings received by a firm and its long-run post-SEO operating performance. This is the last hypothesis that we test here (**H6**).

3.4 Data and Sample Selection

3.4.1 Online Employee Ratings Data

We obtain employee ratings from Glassdoor, one of the largest job site in the US. Glassdoor was launched in June 2008 and provides information about companies that is posted by current and former employees, including company ratings, compensation and benefits, and interview experiences. Hundreds of thousands of users have posted over 33 million ratings and insights for approximately 700,000 companies around the world on the Glassdoor website. The website is widely used and had 45 million global users visit in July 2017.[12] Each company's review contains numerous rating measures: an overall rating, senior management rating, compensation and benefits rating, and company culture and values rating, all of which are measured on a five point scale.

Measures of Online Employee Ratings

We use the following four ratings available on Glassdoor to construct our main independent variables for empirical analyses: overall rating, management rating, compensation rating, and cultural rating. As we mentioned earlier, employees rate various aspects of the firm where they work: management, work-life balance, culture, compensation, among other things. Overall Rating is the average of overall rating (from a scale of 1 to 5) in each year for each firm rated on Glassdoor over a period of 365 days prior to the equity issue announcement. Similarly, Management Rating is the average of senior management rating (on a scale of 1 to 5); Compensation Rating is the average of compensation and benefits rating (on a scale of 1 to 5); and Cultural Rating is the average of culture and values rating (on a scale of 1 to 5), in each year for each firm, calculated in the same manner. These ratings are important source of information produced by employees and captures various aspects of qualities of firm and its management. Hence, we conjecture that these ratings are good proxies for firm-specific information provided by employees. Table 1 shows the summary statistics of these employee rating measures for the sample of firms having SEOs.

It may be argued that online review data is susceptible to response bias. For example, Luca and Zervas (2016) find that fake or suspicious reviews for restaurants on Yelp are bimodally distributed, which may indicate significant bias in response. However, Glassdoor ratings may not

[12]For more details about site facts and statistics, please visit https://www.Glassdoor.com/press/facts/.

suffer from response bias for two reasons. First, Glassdoor uses a "Give to get" policy as an incentive to encourage more neutral and balanced company ratings. Under this policy, Glassdoor users need to share their own opinion of their employee in order to access information on Glassdoor. Second, Sheng (2019) and our paper show that the Glassdoor ratings are approximately normally distributed, which implies that there may not be any response bias in Glassdoor ratings data. Figure A1 in the appendix shows that the overall ratings for our SEO sample is approximately normally distributed.[13]

Common Factor Analysis of Online Employee Ratings

We use four rating measures available on the Glassdoor website. Each of these measures capture different source of information. We use common factor analysis and create a common rating factor to identify common information available in these ratings. Further, factor analysis reduces the dimensionality of data.[14] All these rating variables are correlated and capture different aspects of employee ratings. With factor analysis, we capture the information content common in all these rating measures. Next, we rotate the initial factors so that each employee rating measure has substantial loadings on as few factors as possible. This methodology is consistent with the implementation of common factor analysis in the literature.[15]

We show the results of our common factor analysis in Table 2. Panel A shows the Eigenvalues of the four factors. We find that only the first factor has Eigenvalue over 1 and explains almost 100% of the variation in the online employee rating measures. Panel B shows the loadings of the four employee rating measures on the first factor. The loading indicate that all the four rating variables load positively on the first factor. Further, the first factor is highly correlated (positively) with all the four rating measures. The last column in Panel B shows the communality, which explains the proportion of variance in each rating measure accounted for by the common factor. Communality is bound between 0 and 1 and shows that our first rating factor captures a large portion of the

[13] We find similar patterns for other rating variables in our SEO sample. We also find similar patterns for our CRSP/Compustat sample.

[14] We prefer the factor analysis approach to the principal component analysis approach. Principal component analysis breaks the covariance matrix between the four rating measures into four orthogonal components. However, our aim is to capture the unobservable common information in the four rating measures. Hence, we use the common factor analysis approach. Our results are robust to using principal component analysis.

[15] A number of papers in the empirical finance literature have used common factor analysis to isolate information common to several proxy variables. See, e.g., Guay (1999) and Chemmanur and Paeglis (2005).

variation in each of the rating measures. We use this first rating factor as an additional measure of employee ratings in our analyses.

3.4.2 SEO data

Our sample of SEOs from 2008 to 2017 is obtained from the Thomson One Global New Issues database. We drop all financial firms (all firms with SIC codes between 6000 and 6999), utility firms (SIC codes between 4900 and 4999) since they may be issuing equity to meet regulatory requirements. Following Kim and Purnandam (2014), we drop all observations with offer price below $1. We match this dataset with our matched Glassdoor/CRSP/Compustat dataset and are left with 1,052 issues made by 615 firms. We include all the offerings announcements made by a firm in a year.[16] If a firm had multiple issues following an offerings announcement, we keep the earliest issue made by the firm.[17] For each SEO of a sample firm, we report announcement returns (CAR) over a three-day window (-1, +1) centered on the announcement date. Following existing literature, we use filing date from the Thomson One Global New Issues database as the announcement date.[18] We compute CAR in following way. We compute announcement returns (*CAR (CRSP Value Weighted)*) by subtracting the value-weighted CRSP market return from raw daily returns of issuing firms and aggregate it over the 3-day window around the announcement.[19] Further, we compute Glassdoor ratings for each firm around their SEO by calculating the average rating over a period of 365 days prior to SEO announcement. Table 1 shows the summary statistics of the subsample of Glassdoor-rated firms around their SEOs. We report announcement returns for SEOs and corresponding firm characteristics around SEOs. A median firm has negative announcement returns (-2 percent CAR). About, 35 percent of SEOs have positive announcement effect.

[16]Our results also hold if we include only the first offering made by a firm in a year when the firm had multiple offerings.

[17]Our results hold when we consider multiple issues following an offering announcement by a firm.

[18]Kim and Purnandam (2014) notes that majority of the announcement dates are same as the filing dates mentioned in the Thomson One database. As a robustness test, we also computed announcement returns over different windows, (-2, +1); (-1, +2); and (0, +1). Our results are robust to these windows.

[19]Our results are robust to computing announcement returns by using the Fama and French 5X5 size and book-to-market matched portfolio return as the benchmark market return rather than using value-weighted CRSP market return.

3.4.3 Accounting Data

We extract employee ratings given for 2,842 public companies with headquarters at the U.S. over the period 2008 to 2017. We match this dataset to the daily stock price dataset from the Center for Research in Security Prices (CRSP) database. Additionally, we use the Compustat database to obtain information on other characteristics of firms like asset size, equity issues and repurchases, debt issues and reductions, tobin's q, and other characteristics. After this matching, we are left with 18,327 firm-year observations for 2,644 firms. For each firm for each year, we compute Glassdoor ratings by calculating the average rating over a period of 365 days prior to reporting of annual 10-K reports.

3.5 Empirical Analyses and Results: Baseline Analyses

3.5.1 The Relation between the Announcement Effect of an Equity Issue and the Realization of Online Employee Ratings

In this section, we study the relation between employee ratings and announcement returns around filings of SEOs, which correspond to our hypothesis **H1**, and the relation between employee ratings and the probability of positive announcement returns around SEOs, which correspond to our hypothesis **H2**. We estimate the following OLS model when the dependent variable is cumulative abnormal returns:

$$CAR_{i,t} = \alpha_0 + \alpha_1 Employee\ Rating_{i,t} + X_{i,t} + \epsilon_{i,t}, \tag{3.4}$$

and the following logistic regression model when the dependent variable is the probability of positive announcement return:

$$Positive\ Abnormal\ Return_{i,t} = \alpha_0 + \alpha_1 Employee\ Rating_{i,t} + X_{i,t} + \epsilon_{i,t}, \tag{3.5}$$

where i indexes firm and t indexes year. To study the relation between SEO announcement returns and online employee ratings, we use the standard measure of announcement returns, cumulative abnormal return (CAR), as the dependent variable in the above model. To study the relation between the probability of positive SEO announcement returns and online employee ratings, we use an indicator variable as the measure of positive announcement returns. The indicator (*Positive Abnormal Return*) takes the value 1 when the CAR around the SEO is greater than zero, otherwise it takes the value 0. Our explanatory variable of interest is *Employee Rating*, which represents the four rating measures on Glassdoor and the common rating factor. X represents a vector of controls, which are described below.

We control for sales (*Ln(Sale)*), firm age (*Ln(Age)*), market to book (*Tobin's Q*), size of the equity issue (*Offer Size*), sales growth (*Sales Growth*), R&D expenditure (*R&D/Sale*), past 12-month stock return (*Prior Return*), and profitability (*Profitabiity*), which are standard controls used in the literature. We include 2-digit SIC industry code by filing year and state fixed effects in our regressions to account for heterogeneity due to these factors. We cluster standard errors at the industry by filing year level since residuals may be correlated across observations within an industry in a year.

We present our results of the above tests in Table 3. In Panel A, our dependent variable is cumulative abnormal return. In Columns (1), (2), and (5), we show that the coefficients of overall rating, management rating, and the common rating factor are positive and significant at the 5 percent, 5 percent, and 10 percent levels, respectively. The coefficient of compensation rating and cultural rating are positive, but insignificant. Our results are also economically significant: a one standard deviation increase in overall rating is associated with a 1.7 percentage point increase in the announcement return. Further, a one standard deviation increase in the common rating factor is associated with 1.7 percentage point increase in the announcement returns. This is substantial as the announcement returns (CAR) for the median firm is -2 percent. These results suggest that firms with better online employee ratings have higher SEO announcement returns, which supports our hypothesis **H1**.

In Panel B of Table 3, our dependent variable (*Positive Abnormal Return*) takes the value 1 if CAR is positive, and takes the value 0 otherwise, in a logistic regression. In Columns (1), (2), (4), and (5), we show that the coefficients of overall rating, management rating, cultural rating, and the common rating factor are positive and significant at the 1 percent, 1 percent, 10 percent, and 5 percent levels, respectively.[20] The coefficient of compensation rating is positive, but insignificant. Our results are also economically significant. A one standard deviation increase in overall rating is associated with a 6.7 percentage point increase in the probability of positive announcement return. This is equivalent to an increase of 19.2 percentage in the average firm's probability of positive

[20]Our results are robust to using a linear probability model as shown in Table A2 in the appendix.

abnormal announcement returns. Further, a one standard deviation increase in the common rating factor is associated with a 7.1 percentage point increase in the probability of positive announcement return. These results suggest that firms with better online employee ratings have higher probability of positive SEO announcement returns, which supports our hypothesis **H2**.

3.5.2 The Relation between the Propensity to Issue Equity rather than Debt and the Realization of Online Employee Ratings

We study the relation between online employee ratings and debt versus equity issuance by public firms, corresponding to our hypothesis **H3**, by estimating the following logistic regression model:

$$Issue_{i,t} = \alpha_0 + \alpha_1 Employee\ Rating_{i,t} + X_{i,t} + \epsilon_{i,t}, \tag{3.6}$$

where i indexes firm and t index time. *Issue* is an indicator variable which takes the value one if the firm issues equity in the year and zero if the firm issues debt. Our explanatory variable of interest is *Employee Rating*, which represents the four rating measures on Glassdoor and the common rating factor. X represents a vector of controls, which are described below.

Following Chang, Dasgupta, and Hillary (2006) and Hovakimian, Opler, and Titman (2001), we construct a measure of equity vs. debt issue. We define an indicator variable which takes the value one if a firm issues equity in a fiscal year and zero if the firm issues debt. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by the total book assets at the beginning of the fiscal year exceeds 1 percent.[21] Following the existing literature, observations where firms issue both equity and debt in a given fiscal year as well observations where firms issue neither debt nor equity are dropped.[22] We include the standard controls in our regressions: asset tangibility (*Tangible Asset*),size (*Ln(Asset)*), profitability, past 12-month stock return, sales growth, and age following the existing literature. We include industry by filing year and state fixed effects in our regressions and cluster standard errors at the industry by year level.

We present our results of the above regressions in Table 4. In Columns (1), (2), (3), and (5), we show that the coefficients of overall rating, management rating, compensation rating, and the common rating factor are positive and significant at the 10 percent, 10 percent, 5 percent, and 10

[21] Our results also hold if we only consider debt (equity) issues when debt (equity)/total book assets exceed 5 percent.

[22] Our results are similar when we use data on new equity issues and new debt issues from the Thomson One database.

percent levels, respectively.[23] Our results are also economically significant: a one standard deviation increase in overall rating is associated with a 1.6 percentage point increase in the probability of issuing equity over debt. This is equivalent to an increase of 5.5 percent in the average firm's probability of issuing equity rather than debt. Further, a one standard deviation increase in the common rating factor is associated with a 2 percentage point increase in the probability of issuing equity over debt. These results suggest that firms with better online employee ratings are associated with greater preference of issuing equity over debt, which supports our hypothesis **H3**.

3.5.3 The Relation between the Future Firm Investment Levels and the Realization of Online Employee Ratings

In this section, we study the relation between online employee ratings and investment after SEOs, which correspond to our hypothesis **H4**. We therefore estimate the following model:

$$Investment_{i,t+1} = \alpha_0 + \alpha_1 Employee\ Rating_{i,t} + X_{i,t} + \epsilon_{i,t+1}, \tag{3.7}$$

where i indexes firm and t indexes year. To study the relation between investments and online employee ratings, we measure investment (*Investment*) after the SEO as the ratio of capital expenditure at the first fiscal year after SEO over the level of tangible asset at the previous fiscal year, i.e., one-year lagged value of tangible asset. Our explanatory variable of interest is *Employee Rating*, which represents the four rating measures on Glassdoor and the common rating factor. X represents a vector of controls, which are described below.

We control for sales, firm age, market to book, size of the equity issue, sales growth, R&D expenditure, past 12-month stock return, and profitability. We include industry by filing year and state fixed effects in our regressions and cluster standard errors at the industry by year level.

We present our results of the above tests in Table 5. In Columns (1) to (5), we find that the coefficients of overall rating, management rating, compensation rating, cultural rating, and the common rating factor, are positive and significant at the 5 percent, 5, percent, 1 percent, 1 percent, and 5 percent levels, respectively. Our results are also economically significant. A one standard deviation increase in overall rating is associated with an increase of 6 percentage point in investment in a firm in the next year. This implies a 11.3 percent increase in investment for an

[23] Our results are robust to using a linear probability model as shown in Table A3 in the appendix.

average firm. Further, one standard deviation increase in the common rating factor is associated with an increase of 11.9 percentage point in firm-investment. These results suggest that firms with better online employee ratings have higher level of investment due to lower cost of capital, which supports our hypothesis **H4**.

3.5.4 The Relation between Institutional Investor Participation in SEOs and the Realization of Online Employee ratings

In this section, we study the relation between online employee ratings and the participation of institutional investors in SEOs, which correspond to our hypothesis **H5**. We therefore estimate the following model:

$$\# \, \textit{Institutional Investors}_{i,t+1} = \alpha_0 + \alpha_1 \textit{Employee Rating}_{i,t} + X_{i,t} + \epsilon_{i,t+1}, \tag{3.8}$$

where i indexes firm and t indexes year. To study the relation between the participation of institutional investors and employee ratings, we measure the number of institutional investors owning shares of a firm in the first fiscal quarter after the SEO (*Institutional Investors*). Our explanatory variable of interest is *Employee Rating*, which represents the four rating measures on Glassdoor and the common rating factor. X represents a vector of controls, which are described below.

We control for sales, firm age, market to book, profitability, sales growth, and the past 1-year stock return. We include industry by filing year and state fixed effects in our regressions and cluster standard errors at the industry by year level.

We present our results of the above tests in Table 6. In Columns (1), (2), and (3), we find that the coefficients of overall rating and compensation rating are positive and significant at the 5 percent, 10 percent, and 5 percent levels, respectively. The coefficients of cultural rating and the common rating factor are positive, but insignificant. Our results are also economically significant. A one standard deviation increase in overall rating is associated with an increase of 10 institutional investors investing in a firm. For the median firm, this implies a 10 percent increase in institutional investor participation. These results suggest that firms with better online employee ratings have greater participation of institutional investors at SEOs, which supports our hypothesis **H5**.

3.5.5 The Relation between long-run post-SEO Operating Performance and the Realization of Online Employee Ratings

In this section, we study the relation between online employee ratings and long-run operating performance after SEOs, which correspond to our hypothesis **H6**. We therefore estimate the following model:

$$Operating\ performance_{i,t+3} = \alpha_0 + \alpha_1 Employee\ Rating_{i,t} + X_{i,t} + \epsilon_{i,t+3}, \tag{3.9}$$

where i indexes firm and t indexes year. To study the relation between operating performance and online employee ratings, we measure operating performance after the SEO as the ratio of operating income before depreciation plus interest income (Compustat item 13 and 62 respectively) to the book value of total assets (item 6) averaged over the three consecutive fiscal years after the SEO (*Operating Performance*).[24] Our explanatory variable of interest is *Employee Rating*, which represents the four rating measures on Glassdoor and the common rating factor. X represents a vector of controls, which are described below.

We control for sales, firm age, market to book, R&D expenditure, pre-SEO operating performance level (*OIBDA*), and the past 1-year stock return. We include industry by filing year and state fixed effects in our regressions and cluster standard errors at the industry by year level.

We present our results of the above tests in Table 7. In Columns (2), (4), and (5) we show that the coefficients of management rating, cultural rating, and the common rating factor are positive and significant at 5 percent levels. The coefficients of overall rating and compensation rating are positive, but insignificant. Our results are also economically significant. A one standard deviation increase in the common rating factor is associated with an increase of 6.2 percentage point in the operating performance of a firm. This is substantial as the mean value of operating performance measure is -0.07. These results suggest that firms with better online employee ratings have greater operating performance, which supports our hypothesis **H6**.

[24] Our results are also robust if we adjust the operating performance measure with the industry-wide operating performance by subtracting contemporaneous industry (two-digit SIC code) median operating income ratio from the firm-level operating income ratio.

3.6 Identification Strategy

Our baseline analyses may suffer from some endogeneity concerns. It may be argued that our baseline analysis results reflect only the correlation between online employee ratings and intrinsic firm value, rather than online ratings changing the underlying information environment (causing firms to have algebraically higher SEO announcement effects; greater probability of a positive SEO announcement effect; and most important, causing them to change their external financing policies in favor of issuing equity rather than debt). To address these endogeneity concerns, we make use of staggered implementation of Anti-SLAPP laws, which protect the First Amendment Rights of the people, across U.S. states. The provision of anti-SLAPP laws in some states may affect the propensity of individuals to provide online ratings for firms and to provide relevant information on online platforms. Further, these laws (or their absence) are unlikely be correlated with firm quality.[25] We define the anti-SLAPP laws in detail in the following subsection and describe our empirical approach using these laws.

3.6.1 Anti-SLAPP Laws

SLAPP (strategic lawsuit against public participation) is a retaliatory lawsuit filed against an opponent or critic who had spoken against the plaintiff in a public forum.[26] Such lawsuits are usually filed to intimidate and silence the opponents, who are discouraged by trials which are expensive and time consuming.[27] Critics of SLAPP argue that it is a disguised as civil lawsuit under the pretext of defamation, or conspiracy, or invasion of privacy among the most likely used legal theories. Judge J. Nicholas Colabella wrote in Gordon v. Marrone (N.Y . 1992), "Short of a gun to the head, a greater threat to First Amendment expression can scarcely be imagined." Absence of anti-SLAPP laws may have "chilling-effect," which is defined as suppression of free-speech and associated rights protected by the First Amendment because of a threat of legal sanction. The

[25] We also show in Table A9 in our appendix that the passage of anti-SLAPP laws across states are uncorrelated to their local economic or political factors.

[26] Professors George W. Pring and Penelope Canan coined the term SLAPP in their book 'SLAPPs: Getting Sued for Speaking Out' (1996).

[27] SLAPP suits may have substantial legal and time costs. Under American rule, each party involved in litigation has to bear its legal fees unless there are exceptions like anti-SLAPP statutes in states. SLAPP suits may incur high legal fees: https://www.nytimes.com/2010/06/01/us/01slapp.html Further, another news article mentions that on average, SLAPP suits take two years to go through Court Systems: https://www.heraldtribune.com/news/20080616/critic-sued-by-plaza-hotel-developer.

Supreme Court, in Columbia v. Omni Outdoor Advertising (1991), established the burden on plaintiffs to prove that defendant's petitioning has no merits.[28] Even though this ruling protected the First Amendment Rights, defendants in SLAPP suits may still end up bearing high legal costs. Thus, the threat of litigation may be enough to have a chilling-effect. Anti-SLAPP laws deal with these issues by making plaintiffs responsible for attorney fees of defendants in case of frivolous lawsuits, which are dealt with quickly.

As of January 2019, 28 states have anti-SLAPP statutes (written laws): they are Arizona, Arkansas, California, Connecticut, Delaware, Florida, Georgia, Hawaii, Illinois, Indiana, Kansas, Louisiana, Maine, Maryland, Massachusetts, Missouri, Nebraska, Nevada, New Mexico, New York, Oklahoma, Oregon, Pennsylvania, Rhode Island, Texas, Tennessee, Utah, Vermont.[29] In addition there are anti-SLAPP statutes in the District of Columbia and Guam.[30] In Table 8, we show the states which have enacted anti-SLAPP laws and the corresponding years in which these laws were enacted. Similarly, in Figure 1, we show the map of states with anti-SLAPP laws and states without anti-SLAPP laws. These anti-SLAPP laws were enacted to protect the First Amendment Constitutional rights of citizens. These laws protect the free speech through a variety of ways: frivolous lawsuits are dropped, mandatory coverage of defendant's legal fees by the plaintiff, immediate appeal against denial of anti-SLAPP motion. Further, these laws place additional burden on plaintiffs to establish the merit of their case.

The Impact of Anti-SLAPP Laws on the number of Glassdoor Reviews and on Glassdoor Ratings

Anti-SLAPP protection also applies to online reviews.[31] We expect that online ratings given for firms headquartered in states protected by anti-SLAPP laws may have more information content. Anonymous reviewers for such firms will be less affected by threat of litigation (e.g., defamation lawsuit) compared to reviewers for firms headquartered in states with no anti-SLAPP laws (re-

[28] Please refer this article: https://www.mtsu.edu/first-amendment/article/1019/slapp-suits.

[29] Recently, some more states have implemented the anti-SLAPP laws. For example, Colorado in 2019 and Virgina in 2020. Virginia had passed weak anti-SLAPP laws in 2017, which did not offer much protection.

[30] In two U.S. states anti-SLAPP statutes have been struck down as unconstitutional. The Washington State statute (enacted in 2010) was declared unconstitutional in 2015. The Minnesota anti-SLAPP statute (enacted in 1994) was declared unconstitutional in 2017. In both the cases, the respective Supreme Court judges ruled that the anti-SLAPP statutes violated the constitutional rights of plaintiffs to have a civil jury trial.

[31] Glassdoor website mentions that they fund anti-SLAPP motions on the behalf of anonymous reviewers : https://www.glassdoor.com/blog/glassdoor-protect-anonymous-free-speech/.

viewers for these firms are more likely to be affected by the chilling effect of litigation threat). Anonymous reviewers face credible litigation threats. There have been instances where courts have ordered Glassdoor to reveal the identity of anonymous reviewers, which were later overruled by higher courts in some cases.[32] Further, Glassdoor website mentions some measures it takes to protect the identity of its anonymous reviewers including filing anti-SLAPP motions on their behalf. This implies that Glassdoor reviwers are likely to be aware of anti-SLAPP laws, which protect their First Amendment Rights.[33] Hence, outside investors may put greater weight on the information contained in online employee ratings for firms headquartered in states with anti-SLAPP laws.

In Table 9, We show the impact of anti-SLAPP laws on the number of Glassdoor reviews and on Glassdoor ratings. Our sample is a firm-year panel comprising all public firm rated on Glassdoor between 2008 to 2017. In Panel A of Table 9, the dependent variables are the raw number of Glassdoor reviews and normalised number of Glassdoor reviews, respectively. Raw number of Glassdoor reviews is the number of reviews given by employees of a firm on the Glassdoor website in a year, while the normalized number of reviews is industry-adjusted number of Glassdoor reviews for a firm in a year scaled by the standard deviation of Glassdoor reviews across firms in a particular industry. We show that after the passage of anti-SLAPP laws there is increase both the raw number of reviews and the normalized number of reviews for firms on Glassdoor. This result supports our intuition that anti-SLAPP laws lead to greater participation by reviewers on the Glassdoor website. In Panel B of Table 9, the dependent variables are the five rating variables: four Glassdoor ratings variables and one common rating factor. In column (4) and Column (5), we show that the passage of anti-SLAPP laws lead to lower cultural rating (significant at 1% level) and lower common rating factor (significant at 5% level). For the other ratings variables, the coefficients are negative but not significant. We expect a negative relation between anti-SLAPP laws and Glassdoor ratings because the anti-SLAPP laws may encourage reviewers (employees) with negative views about their firms to express their opinion online (in the form of lower Glassdoor ratings).

Given that we establish the impact of anti-SLAPP laws on the participation of reviewers on Glassdoor and on Glassdoor ratings, we next show the impact of anti-SLAPP laws on firms' external

[32] Please refer following links for more details: https://www.shrm.org/resourcesandtools/legal-and-compliance/employment-law/pages/glassdoor-identities.aspx, https://clearviewpost.com/employer-sues-glassdoor-over-identity-of-anonymous-former-employee/, and https://cdt.org/blog/anonymous-speech-online-dealt-a-blow-in-us-v-glassdoor-opinion/.

[33] Please refer appendix for greater details on measures taken by Glassdoor to protect its anonymous reviewers.

financing and investment policies to establish that our baseline results are causal.

3.6.2 Difference in Differences (DID) Analysis

We use a DID approach to examine how the staggered implementation, and in some cases rejection, of anti-SLAPP laws in U.S. states affect SEO announcement returns, probability of positive SEO announcement returns, equity versus debt issues by firms, and firms' investment level after SEOs. We have two group of firms: firms headquartered in states with anti-SLAPP laws in a given year and firms headquartered in states without anti-SLAPP laws in a given year. We use the following empirical specification:

$$Outcome_{i,t} = \alpha_1 Anti\text{-}SLAPP_{i,t} + \ X_{i,t} + \epsilon_{i,t}. \tag{3.10}$$

where i indexes firm, s indexes firm-headquarter state, and t indexes year. *Outcome* refers to the four dependant variables, namely, announcement returns, probability of positive announcement returns, equity versus debt issues by firms, and firms' investment level after SEOs. *Anti-SLAPP* is an indicator variable, which takes the value 1 if the firm-headquarter state have anti-SLAPP laws in that year and takes the value 0, otherwise.[34] X refers to the control variables, which are same as in our baseline OLS specification. We use firm-headquarter state and industry by filing year fixed effects in our specification. We cluster standard errors by firm-headquarter state since anti-SLAPP indicator is a state-level variable (Betrand, Duflo, and Mullainathan (2004)). We expect that the coefficient to be positive. This is because we expect online employee ratings to have greater information content after the passage of anti-SLAPP laws. and also due to greater participation by reviewers on Glassdoor. The underlying assumption in our identification strategy is that the passage of anti-SLAPP laws are exogenous to firm outcomes, which is plausible as these anti-SLAPP laws are implemented to protect the First Amendment Rights of U.S. citizens. Indeed, we show in Table A9 in our appendix that local economic or political factors did not affect passage

[34] Two states, Minnesota and Washington State, passed anti-SLAPP laws that were scrapped by their respective Supreme Courts. We assign a value of 1 to anti-SLAPP law indicator in those two states during the period in which anti-SLAPP laws were applicable there. Our results are robust to dropping firms that are headquartered in the above two states. Further, Colorado and West Virgina had case laws in our sample period that offer some protection to defendants though not as much as the anti-SLAPP laws. For example, case laws in above states did not provide for mandatory recovery of attorney fees for defendants in case of frivolous lawsuits. Our results are also robust to dropping firms that are headquartered in the above two states. Lastly, our results are robust to considering only those anti-SLAPP laws which provide provision for reimbursement of attorney fees. 24 out of 28 states in our sample have anti-SLAPPs laws with above provision, and our results are robust to only considering such anti-SLAPP laws.

of anti-SLAPP laws across states.

In order to ensure that firms headquartered in anti-SLAPP laws states (treated group) are similar to firms headquartered in non anti-SLAPP laws states (control group), we use propensity score matching, using the one-to-one nearest neighbors methodology with common support, to create a matched group. We do this matching to ensure that treated and control groups are similar on observable.[35] We match firms based on their sales, age, market to book, profitability, sales growth, and past 1 year stock returns. Table 10 shows the characteristics of the the two groups (treated and control) before and after the matching. Panel A of Table 10 shows that prior to matching treated and control group of firms are statistically different on size and market to book. Panel B of Table 10 shows that, after matching, treated and control group of firms are statistically indistinguishable as per the observable covariates. Next, after matching, we conduct our DID analysis.

We now show our results using the DID approach.

Identification Test: DID Analysis of the Relation between Anti-SLAPP Laws and Announcement Effects of Equity Issues

In this section, we show the effect of anti-SLAPP laws on announcement returns around SEOs and probability of positive announcement returns, respectively, for firms using a DID approach, which correspond to our hypotheses **H1** and **H2**, respectively. We use the same set of independent variables and controls as in our baseline (OLS) analysis. We include fixed effects for industry by filing year and firm-headquarter state in our regressions to account for heterogeneity due to these factors. We cluster standard errors at the state level.

We present our results of the above tests in Table 11. The main variables of interest is the indicator variable for the anti-SLAPP laws. We expect online employee ratings to be more informative post the passage of anti-SLAPP laws, thereby expecting the coefficient of anti-SLAPP indicator to be positive and significant. In Columns (1) and (2), we run a linear regression and a logistic regression, respectively. We show that the passage of anti-SLAPP laws leads to higher SEO announcement returns (positive and significant at 1% level) and greater probability of positive

[35]Our results are robust to using the full unmatched sample, which we show in tables A3, A4, and A5 in the appendix.

announcement returns (positive and significant at 1% level). These results suggest that information content in online employee ratings is greater for firms after anti-SLAPP laws are implemented in firm-headquarter states and these firms, in turn, have higher SEO announcement returns and greater probability of positive announcement returns, which supports our hypotheses **H1** and **H2**, respectively.

Identification Test: DID Analysis of the Relation between Anti-SLAPP Laws and the Propensity to Issue Equity rather than Debt

In this section, we show the the effect of anti-SLAPP laws on the probability of issuing equity rather than debt for firms using a DID approach, which correspond to our hypothesis **H3**. We use a logistic regression model like in our baseline regression. We use the same set of independent variables and controls as in our baseline (OLS) analysis. We include fixed effects for industry by filing year and firm-headquarter state in our regressions to account for heterogeneity due to these factors. We cluster standard errors at the state level.

We present our results of the above tests in Table 12. We expect the coefficient of anti-SLAPP indicator to be positive and significant. In Column (1), we show that the coefficients of anti-SLAPP indicator indicator is positive and significant at 1 percent level. This results suggest that information content in online employee ratings is greater for firms after the anti-SLAPP laws are passed in firm-headquarter states and these firms, in turn, have greater probability of issuing equity rather than debt, which supports our hypothesis **H3**.

Identification Test: DID Analysis of the Relation between Anti-SLAPP Laws and the Future Firm Investment Level

In this section, we show the the effect of anti-SLAPP laws on investment level of firms after SEOs, which correspond to our hypothesis **H4**. We use the same set of independent variables and controls as in our baseline (OLS) analysis. We include fixed effects for industry by filing year and firm-headquarter state in our regressions to account for heterogeneity due to these factors. We cluster standard errors at the state level.

We present our results of the above tests in Table 13. We expect the coefficient of anti-SLAPP indicator to be positive and significant. In Column (1), we show that the coefficients of anti-

SLAPP indicator indicator is positive and significant at 5 percent level. This results suggest that information content in online employee ratings is greater for firms after anti-SLAPP laws are implemented in firm-headquarter states. This in turn, lowers the cost of equity for firms, i.e., higher SEO announcement effect (as we show in Table 11). Consequently, some projects which were earlier negative NPV may become positive NPV for above firms (due to lower cost of capital), and these firms, in turn, have higher future investment level, which supports our hypothesis **H4**.

Our DID analyses support our baseline analyses and suggest that online employee ratings affect the information environment of firms, leading to higher announcement effects, greater probability of positive announcement effects, greater propensity of a firm to issue equity rather than debt to raise external finance, and higher future investment level.

We now address some common concerns associated with a DID approach.[36] In our empirical specification, we ensure that treated and control groups are similar on observable covariates (due to matching). As we show in our appendix, our results hold for entire unmatched sample too. Further, we conduct a time-trend analysis to ensure that there is no reverse causality and that our results satisfy the parallel trends assumption. Our results show that there is no trend in the announcement effect prior to the implementation of anti-SLAPP laws in various states. We now discuss our results of the time-trend analysis.

Timing of Changes in Announcement Return around Implementation of Anti-SLAPP Laws

In order to test the parallel trend assumption for our DID approach, we replace the variable for whether the state has in which a firm is headquartered has passed the anti-SLAPP law in year t with the following indicator variables: *T=-4*, *T=-2*, *T=0*, *(*T=+2), and *T=2+ and onwards*. *T=-4* and *T=-2* are variables set to one for firms headquartered in states in year 4 and year 3 and year 2 and year 1, respectively, prior to the passage of anti-SLAPP laws in those states; otherwise zero. *T=0* is an indicator variables that is equal to one in the year Anti-SLAPP law is implemented in

[36] Online employee rating may have a causal effect on institutional investor participation and post-SEO operating performance of firms as well, since firms with higher employee ratings face a lower cost of external financing and have higher level of investment. This, in turn, may lead to better future post-SEO operating performance. However, the effect of employee ratings on the above variables, namely, institutional investor participation and post SEO-operating performance, are likely to be of second order so that we find much weaker results in our identification tests for these two variables.

a firm-headquarter state; otherwise zero. T=+2 is an indicator variable that is equal to one in the years 1 and 2 after the implementation of Anti-SLAPP law in a firm-headquarter state; otherwise zero. T=2+ and onwards is an indicator variable that is equal to one in the year 3 and beyond after the implementation of Anti-SLAPP law in a firm-headquarter state; otherwise zero. We include all the controls and fixed effects used in our baseline analyses. Consistent with parallel trends assumption, we show in Table 14 that there are no trends in cumulative abnormal returns prior to the implementation of anti-SLAPP laws. We find that coefficients of *(*T=+2) and *T=2+ and onwards* are positive and significant (at 1% levels) while the coefficients of other indicator variables are insignificant. This evidence shows that there is no pre-trend in our results and the impact of Anti-SLAPP laws on firms' financial and investment policies occur only after the passage of these laws.[37] This result also shows that reverse causality concerns may not apply in our setting. It is the implementation of anti-SLAPP laws, which is driving the effect on financial and investment policies of firms.

Cross-sectional Evidence

We also provide cross-sectional evidence in Table A8 of our appendix which suggests that the effect of Glassdoor ratings is stronger for firms after the staggered passage of anti-SLAPP laws in firm-headquarter states. We regress our dependent variables (announcement effect, probability of positive announcement effect, and equity vs. debt issue) on the interaction of Glassdoor ratings variables and anti-SLAPP indicator along with other controls, and show that the coefficients of interaction variables are positive (Table A8 in in the appendix).[38] The above test suggests that the same level of Glassdoor employee ratings is much more informative for firms headquartered in states with anti-SLAPP laws, which is expected.

3.6.3 No evidence of Manipulation of Glassdoor Ratings prior to Equity Issues

It is possible that firms may inflate their Glassdoor ratings prior to equity issues by encouraging their employees to provide favorable review on Glassdoor, which may lead to favorable perception of

[37] We conduct similar analyses for our other outcomes of interest, namely, probability of positive returns, debt versus equity issues, and future investment levels. Our results are similar though slightly weaker.

[38] We discuss these results in greater detail in section A4 of our appendix.

firms among investors.[39] If there is manipulation of ratings, we would expect firms to have positive jumps in ratings before their equity issues. We conduct a time-trend analysis of Glassdoor ratings of firms around their equity issues. We do not find any evidence of jumps in Glassdoor ratings of firms around their equity issues, which suggests that there is no manipulation of ratings by firms, on average, around equity issues. Our sample is a firm-year panel that includes all firms with Glassdoor ratings that have issued equity between 2008 and 2017. In Table A7, in the appendix, we regress our five Glassdoor rating measures, four rating variables and one common rating factor, on time trends (pre- and post-SEO) and other controls. We show that almost all indicator variables for time trends, before and after equity issue are insignificant. In particular, the indicator variables for time trends prior to equity issues are insignificant. This empirical evidence rules out manipulation of ratings by firms, on average, prior to their equity issues.[40]

3.7 Conclusion

In this paper, we analyze the effects of equity market investors having access to online employee ratings of firms, on their external financing and investment policies. We develop testable hypotheses using a theoretical framework in which the insiders of a firm have private information about its intrinsic value, but where outsiders have access to soft information signals imperfectly correlated with this intrinsic firm value. We test these hypotheses using a large sample of around 1.1 million employee ratings from the Glassdoor website covering a sample of 2842 public firms during 2008 to 2017. We find that firms with higher average online employee rating realizations are associated with algebraically greater abnormal stock returns upon an equity issue announcement; a greater propensity to have positive abnormal stock returns upon such an announcement; a greater propensity to choose equity over debt to raise external financing; higher annual investment expenditures; greater participation by institutional investors in their SEOs; and better long-run post-SEO operating performance.

Our identification strategy relies on the variation across U.S. states in laws protecting the First Amendment Rights of citizens (anti-SLAPP laws). We use the staggered passage, and in some

[39] For example, the following Wall Street Journal report claims that some companies manipulate their Glassdoor ratings around deadline for Glassdoor best-workplace award. Please refer: https://www.wsj.com/articles/companies-manipulate-glassdoor-by-inflating-rankings-and-pressuring-employees-11548171977.

[40] We discuss this result in greater detail in section A5 of our appendix.

cases rejection, of anti-SLAPP laws across U.S. states in a DID approach to show that anti-SLAPP laws have greater effect on announcement returns, positive announcement effect, equity vs. debt issues, and investment levels of firms. Anti-SLAPP laws mitigate chilling-effect leading to greater information content in online employee of firms headquartered in states with anti-SLAPP laws. Further, we show that the staggered passage of anti-SLAPP laws lead to increase in number of reviews by employees on Glassdoor and also lead to lower ratings on Glassdoor (potentially due to greater participation of employees with negative views). We also provide cross-sectional evidence that the impact of Glassdoor ratings are stronger after the passage of anti-SLAPP laws across U.S. states. Lastly, we rule out the manipulation of Glassdoor ratings around equity issues of firms. Thus, we show that there is information content in online employee rating realizations that causally leads to higher announcement effects; higher probability of having a positive announcement effect; greater propensity to issue equity rather than debt; and higher future investment levels for firms.

References

Aggarwal, Rajesh K, Laurie Krigman, and Kent L Womack, 2002, Strategic IPO underpricing, information momentum, and lockup expiration selling, *Journal of Financial Economics* 66, 105–137.

Angrist, Joshua D, and Jörn-Steffen Pischke, 2008, *Mostly harmless econometrics: An empiricist's companion* (Princeton university press).

Bajo, Emanuele, Thomas J. Chemmanur, Karen Simonyan, and Hassan Tehranian, 2016, Underwriter networks, investor attention, and initial public offerings, *Journal of Financial Economics* 122, 376 – 408.

Benveniste, Lawrence M, and Paul A Spindt, 1989, How investment bankers determine the offer price and allocation of new issues, *Journal of financial Economics* 24, 343–361.

Besen, Stanley M, and Leo J Raskind, 1991, An introduction to the law and economics of intellectual property, *Journal of Economic Perspectives* 5, 3–27.

Bhattacharya, Sudipto, and Jay R Ritter, 1983, Innovation and communication: Signalling with partial disclosure, *The Review of Economic Studies* 50, 331–346.

Block, Joern H., Geertjan De Vries, Jan H. Schumann, and Philipp Sandner, 2014, Trademarks and venture capital valuation, *Journal of Business Venturing* 29, 525–542.

Cao, Jerry, Fuwei Jiang, and Jay R Ritter, 2013, Patent and Innovation-Driven Performance in Venture Capital-Backed IPOs, Working Paper, University of Florida.

Chemmanur, Thomas, and An Yan, 2009, Product market advertising and new equity issues, *Journal of Financial Economics* 92, 40 – 65.

Chemmanur, Thomas J., 1993, The Pricing of Initial Public Offerings: A Dynamic Model with Information Production, *The Journal of Finance* 48, 285–304.

Chemmanur, Thomas J, and Zhaohui Chen, 2014, Venture capitalists versus angels: The dynamics of private firm financing contracts, *The Review of Corporate Finance Studies* 3, 39–86.

Chemmanur, Thomas J, Manish Gupta, and Karen Simonyan, 2016, Management Quality and Innovation in Private Firms and the IPO Market Rewards to Innovative Activity, Working Paper, Boston College.

Chemmanur, Thomas J, Jie He, Shan He, and Debarshi Nandy, 2018, Product market characteristics and the choice between ipos and acquisitions, *Journal of Financial and Quantitative Analysis* 53, 681–721.

Chemmanur, Thomas J, Shan He, and Debarshi K Nandy, 2009, The going-public decision and the product market, *The Review of Financial Studies* 23, 1855–1908.

Chemmanur, Thomas J, Elena Loutskina, and Xuan Tian, 2014, Corporate venture capital, value creation, and innovation, *The Review of Financial Studies* 27, 2434–2473.

Chemmanur, Thomas J., and Imants Paeglis, 2005, Management quality, certification, and initial public offerings, *Journal of Financial Economics* 76, 331 – 368.

Economides, Nicholas S, 1988, The economics of trademarks, *Trademark Rep.* 78, 523.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist, 2017, What is a Patent Worth? Evidence from the US Patent Lottery, Working Paper, National Bureau of Economic Research.

Faurel, Lucile, Qin Li, Devin M Shanthikumar, and Siew Hong Teoh, 2016, CEO Incentives and New Product Development: Insights from Trademarks, Working Paper, University of California, Irvine.

Gompers, Paul, and Josh Lerner, 2000, Money chasing deals? The impact of fund inflows on private equity valuation, *Journal of Financial Economics* 55, 281–325.

Gompers, Paul A., 1995, Optimal Investment, Monitoring, and the Staging of Venture Capital, *The Journal of Finance* 50, 1461–1489.

Graham, Stuart J.H., Galen Hancock, Alan C. Marco, and Amanda Fila Myers, 2013, The USPTO Trademark Case Files Dataset: Descriptions, Lessons, and Insights, *Journal of Economics and Management Strategy* 22, 669–705.

Graham, Stuart JH, Robert P Merges, Pam Samuelson, and Ted Sichelman, 2009, High technology entrepreneurs and the patent system: Results of the 2008 berkeley patent survey, *Berkeley Technology Law Journal* 24, 1255.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, NBER Working Paper 8498.

Heath, Davidson, and Christopher Mace, 2019, The strategic effects of trademark protection, *The Review of Financial Studies* .

Hsu, David H, and Rosemarie H Ziedonis, 2008, Patents as quality signals for entrepreneurial ventures., in *Academy of Management Proceedings*, volume 2008, 1–6, Academy of Management.

Hsu, Po-Hsuan, Kai Li, Yunan Liu, and Hong Wu, 2017, Product Market Dynamics and Mergers and Acquisitions: Insights from the USPTO Trademark Data, Working Paper, University of British Columbia.

Jain, Bharat A., and Omesh Kini, 1994, The Post-Issue Operating Performance of IPO Firms, *The Journal of Finance* 49, 1699–1726.

Landes, William M., and Richard A. Posner, 1987, Trademark Law: An Economic Perspective, *The Journal of Law and Economics* 30, 265–309.

Lerner, Joshua, 1994, Venture capitalists and the decision to go public, *Journal of Financial Economics* 35, 293–316.

Long, Clarisa, 2002, Patent signals, *The University of Chicago Law Review* 625–679.

Loughran, Tim, and Jay R. Ritter, 1997, The Operating Performance of Firms Conducting Seasoned Equity Offerings, *The Journal of Finance* 52, 1823–1850.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand, 2013, Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt, *American Economic Review* 103, 1797–1829.

Mendonça, Sandro, Tiago Santos Pereira, and Manuel Mira Godinho, 2004, Trademarks as an indicator of innovation and industrial change, *Research Policy* 33, 1385–1404.

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

Ritter, Jay R, and Ivo Welch, 2002, A review of IPO activity, pricing, and allocations, *The Journal of Finance* 57, 1795–1828.

Sampat, Bhaven, and Heidi L Williams, 2019, How do patents affect follow-on innovation? evidence from the human genome, *American Economic Review* 109, 203–36.

Seru, Amit, 2014, Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics* 111, 381–405.

Stock, James H., and Motohiro Yogo, 2002, Testing for Weak Instruments in Linear IV Regression, Working Paper 284, National Bureau of Economic Research.

Tian, Xuan, 2011, The causes and consequences of venture capital stage financing, *Journal of Financial Economics* 101, 132–159.

Tian, Xuan, 2012, The role of venture capital syndication in value creation for entrepreneurial firms, *Review of Finance* 16, 245–283.

Tian, Xuan, and Tracy Yue Wang, 2014, Tolerance for failure and corporate innovation, *The Review of Financial Studies* 27, 211–255.

Zhou, Haibo, Philipp G. Sandner, Simon Luca Martinelli, and Joern H. Block, 2016, Patents, trademarks, and their complementarity in venture capital funding, *Technovation* 47, 14 – 22.

Table 1: Summary Statistics around Seasoned Equity Offerings (SEOs) of Public Firms with Online Employee Ratings on Glassdoor

This table reports summary statistics for the subsample of Glassdoor-rated firms from 2008 to 2017, which made seasoned equity offerings (SEOs). *CAR (CRSP Value-Weighted)* is the three-day cumulative abnormal return centered on the announcement date of SEO, and computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm. *Positive Abnormal Return* is an indicator variable that takes the value 1 if the three-day cumulative abnormal return (CAR) centered on the SEO announcement, computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm, is positive and takes the value 0 of the CAR is non-positive. *Investment* is the ratio of capital expenditure for a firm in a year scaled by the tangible asset of the firm at the beginning of the fiscal year. *# Institutional Investors* is the number of institutional investors investing in a firm at the end of first fiscal quarter after the SEO. *Avg. OIBDA level* is the ratio of the operating income before depreciation plus interest income (Compustat item 13 and 62 respectively) to the book value of total assets (item 6) averaged over the three consecutive fiscal years after the SEO. *Overall Rating* is the average of overall rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year.

Summary Statistics of Firms with Glassdoor ratings around SEOs						
Variables	N	Mean	Std. Dev.	1st Quartile	Median	3rd quartile
CAR (CRSP Value Weighted)	1,042	-0.02	0.12	-0.06	-0.02	0.02
Positive Return (VW)	1,042	0.35	0.48	0	0	1
Investment	828	0.53	4.93	0.11	0.21	0.42
# Institutional Investors	853	150.84	183.24	43	106	180
Avg. OIBDA level	481	-0.07	0.34	-0.18	0.06	0.11
Overall Rating	938	3	0.92	2.46	3	3.67
Management Rating	926	2.74	0.97	2	2.75	3.33
Compensation Rating	927	3.2	0.81	2.71	3.16	3.75
Cultural Rating	594	2.98	0.98	2.4	3	3.6
Ln(Sale)	934	5.47	2.48	3.73	5.62	7.34
Offer Size	1,005	186.58	351.28	16.5	68.19	193.6
Ln(Age)	1,027	2.46	0.92	1.95	2.64	3.04
Tobin's Q	1,008	2.51	1.98	1.26	1.77	3.09
Prior Return	1,052	0.28	0.88	-0.26	0.12	0.56
Profitability	1,009	-0.15	0.41	-0.33	0.03	0.11
Sales Growth	739	0.15	0.38	-0.04	0.1	0.27
R&D/Sales	1,052	0.62	1.52	0	0.01	0.25

Table 2: Extraction of Online Employee Ratings Factor using the Factor Analysis

Table 2 reports our summary statistics of the common factor analysis of the following four rating measures on Glassdoor. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Factor 1*, *Factor 2*, *Factor 3*, and *Factor 4* are the common factors obtained by using factor analysis on the above-mentioned rating variables. *Rating Factor* is the first factor obtained from factor analysis using the four employee rating measures on Glassdoor. Panel A reports the Eigen values for the four factors. Panel B reports the summary statistics for the factor analysis. It includes the loadings on the first factor, correlation between the first factor and the four rating measures, and communality, which captures the proportion of variance of each rating measures explained by the factor. Panel C reports the descriptive statistics of the first factor.

Panel A: Eigen Values

Factor 1	Factor 2	Factor 3	Factor 4
2.909	0.022	-0.003	-0.018

Panel B: Summary for Factor Analysis

Variable	Loadings on 1st Factor	Correlation	Communality
Overall Rating	0.928	0.960	0.862
Management Rating	0.892	0.922	0.796
Compensation Rating	0.691	0.714	0.477
Cultural Rating	0.880	0.910	0.774

Panel C: Summary Statistics of the First Factor

Variables	N	Mean	Std. Dev.	Min	1st Quartile	Median	3rd quartile	Max
Rating Factor	594	0	0.97	-2.22	-0.63	0.05	0.64	2.33

Table 3: The Relation between the Announcement Effect of an Equity Issue and the Realization of Online Employee Ratings

This table reports the OLS regression results of the effect of online employee ratings on abnormal announcement returns around SEOs, and the logistic regression results of the effect of online employee ratings on the probability of positive abnormal announcement returns around SEOs. In Panel A, the dependent variable *Cumulative Abnormal Return (CAR)* is the three-day cumulative abnormal return centered on the announcement date of SEO, and computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm. In Panel B, the dependent variable *Positive Abnormal Return* is an indicator variable that takes the value 1 if the three-day cumulative abnormal return (CAR) centered on the SEO announcement, computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm, is positive and takes the value 0 if the CAR is non-positive. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), firm-headquarter state fixed effects, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: The impact of Glassdoor Ratings on Abnormal Announcement Returns					
	(1)	(2)	(3)	(4)	(5)
Variables	Cumulative Abnormal Return				
Overall Rating	0.018**				
	(0.008)				
Management Rating		0.015**			
		(0.007)			
Compensation Rating			0.008		
			(0.007)		
Cultural Rating				0.013	
				(0.010)	
Rating Factor					0.021*
					(0.011)
Ln(Sale)	0.002	0.002	0.003	0.004	0.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Ln(Age)	0.012**	0.012**	0.013**	0.003	0.005
	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)
Tobin's Q	0.001	0.001	0.002	-0.001	-0.002
	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)
Offer Size	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	0.008	0.009	0.011	0.013	0.010
	(0.018)	(0.018)	(0.018)	(0.025)	(0.026)
R&D/Sale	-0.004	-0.002	-0.002	0.005	0.003
	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)
Prior Return	-0.006	-0.008	-0.006	-0.006	-0.007
	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)
Profitability	-0.014	-0.013	-0.008	-0.029	-0.033
	(0.032)	(0.034)	(0.033)	(0.030)	(0.029)
Observations	538	532	532	303	303
R-squared	0.259	0.250	0.238	0.256	0.269
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: The Impact of Glassdoor Ratings on the Probability of Positive Announcement Returns					
	(1)	(2)	(3)	(4)	(5)
Variables	Positive Abnormal Return (Indicator Variable)				
Overall Rating	0.073***				
	(0.027)				
Management Rating		0.065***			
		(0.024)			
Compensation Rating			0.013		
			(0.037)		
Cultural Rating				0.064*	
				(0.037)	
Rating Factor					0.080**
					(0.037)
Ln(Sale)	0.007	0.012	0.015	0.018	0.016
	(0.022)	(0.023)	(0.023)	(0.034)	(0.034)
Ln(Age)	0.064	0.057	0.062	0.029	0.033
	(0.040)	(0.040)	(0.040)	(0.082)	(0.081)
Tobin's Q	-0.028*	-0.029*	-0.018	-0.037	-0.042
	(0.017)	(0.017)	(0.016)	(0.027)	(0.027)
Offer Size	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	0.031	0.022	0.037	0.092	0.085
	(0.078)	(0.079)	(0.076)	(0.099)	(0.100)
R&D/Sale	-0.001	0.004	0.009	0.003	-0.003
	(0.021)	(0.022)	(0.023)	(0.038)	(0.038)
Prior Return	0.008	0.008	0.014	-0.010	-0.012
	(0.037)	(0.038)	(0.037)	(0.053)	(0.053)
Profitability	-0.036	-0.077	-0.064	-0.165	-0.178
	(0.113)	(0.121)	(0.114)	(0.128)	(0.128)
Observations	441	435	435	242	242
Pseudo R-squared	0.171	0.162	0.152	0.163	0.167
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table 4: The Relation between the Propensity to Issue Equity rather than Debt and the Realization of Online Employee Ratings: Logistic Regression

This table reports the logistic regression results of the effect of online employee ratings on debt versus equity issues of public firms. The indicator variable *Equity vs. Debt* equals one if equity is issued in the fiscal year and zero if debt is issued. Observations where firms issue both equity and debt in a given fiscal year as well as observations where firms issue neither equity nor debt are dropped. *Overall Rating* is the average of overall rating in each year for each firm over a period of 365 days prior to the reporting of annual 10-K report. Similarly, *Management Rating* is the average of senior management rating; *Compensation Rating* is the average of compensation and benefits rating; and *Cultural Rating* is the average of culture and values rating, in each year for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Profitability* is defined as the ratio of the operating income before depreciation and the book value of assets. *Tangible Asset* is the book value of property, plant, and equipment over the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Ln(Asset)* is the natural logarithm of the book value of total assets of a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. Constant (suppressed), firm-headquarter state fixed effects, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables	Equity vs Debt (Indicator Variable)				
Overall Rating	0.021*				
	(0.011)				
Management Rating		0.020*			
		(0.012)			
Compensation Rating			0.032**		
			(0.015)		
Cultural Rating				0.015	
				(0.010)	
Rating Factor					0.018*
					(0.010)
Profitability	-0.171*	-0.170*	-0.162*	-0.224**	-0.226**
	(0.089)	(0.091)	(0.089)	(0.105)	(0.104)
Tangible Assets	-0.292***	-0.290***	-0.306***	-0.347***	-0.345***
	(0.085)	(0.086)	(0.086)	(0.099)	(0.098)
Ln(Age)	-0.064***	-0.064***	-0.062***	-0.064***	-0.064***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Ln(Asset)	-0.070***	-0.070***	-0.072***	-0.065***	-0.066***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Sales Growth	0.107**	0.102*	0.104*	0.094*	0.094*
	(0.054)	(0.056)	(0.057)	(0.055)	(0.055)
Prior Return	0.033	0.029	0.032	0.048*	0.047*
	(0.024)	(0.024)	(0.024)	(0.026)	(0.026)
Observations	1,660	1,647	1,647	1,246	1,245
Pseudo R-squared	0.446	0.444	0.446	0.446	0.447
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table 5: The Relation between the Future Firm Investment Levels and the Realization of Online Employee Rating

This table reports the OLS regression results of the effect of online employee ratings on the firm investment after SEOs. The dependent variable *Investment* is the ratio of capital expenditure for a firm in a year scaled by the lagged value of tangible asset of the firm. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), firm-headquarter state fixed effects, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables			Investment		
Overall Rating	0.065**				
	(0.026)				
Management Rating		0.066***			
		(0.024)			
Compensation Rating			0.067***		
			(0.023)		
Cultural Rating				0.070**	
				(0.031)	
Rating Factor					0.071**
					(0.034)
Ln(Sale)	-0.021	-0.023	-0.018	-0.014	-0.017
	(0.019)	(0.019)	(0.020)	(0.028)	(0.029)
Ln(Age)	-0.028	-0.024	-0.018	-0.077	-0.071
	(0.025)	(0.025)	(0.026)	(0.055)	(0.057)
Tobin's Q	0.055***	0.052***	0.057***	0.051***	0.048***
	(0.012)	(0.012)	(0.012)	(0.015)	(0.015)
Offer Size	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	0.013	-0.006	0.002	-0.003	-0.013
	(0.071)	(0.069)	(0.071)	(0.130)	(0.135)
R&D/Sale	-0.004	-0.011	-0.007	0.026	0.020
	(0.022)	(0.023)	(0.023)	(0.039)	(0.037)
Prior Return	0.057**	0.052**	0.058**	0.017	0.017
	(0.026)	(0.025)	(0.027)	(0.032)	(0.032)
Profitability	0.315***	0.281**	0.294**	0.325**	0.321**
	(0.112)	(0.114)	(0.116)	(0.156)	(0.155)
Observations	459	454	454	253	253
R-squared	0.428	0.437	0.432	0.423	0.422
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table 6: The Relation between Institutional Investor Participation in SEOs and the Realization of Online Employee Ratings

This table reports the OLS regression results of the effect of online employee ratings on the participation of institutional investors at SEOs. The dependent variable *# Institutional Investors* is the number of institutional investors investing in a firm at the end of first fiscal quarter after the SEO. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. Constant (suppressed), firm-headquarter state fixed effects, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables			# Institutional Investors		
Overall Rating	10.562**				
	(5.160)				
Management Rating		9.733*			
		(5.549)			
Compensation Rating			18.445**		
			(7.023)		
Cultural Rating				3.810	
				(6.064)	
Rating Factor					7.457
					(5.925)
Ln(Sale)	45.576***	46.506***	46.708***	58.230***	57.970***
	(6.218)	(6.449)	(6.456)	(8.757)	(8.703)
Ln(Age)	3.817	3.395	5.005	7.769	8.119
	(7.388)	(7.144)	(7.093)	(15.079)	(14.893)
Tobin's Q	5.760	4.758	4.997	11.977**	11.332**
	(3.774)	(3.753)	(3.654)	(5.187)	(5.177)
Prior Return	3.546	4.229	5.301	-1.756	-1.787
	(7.390)	(7.553)	(7.262)	(12.246)	(12.290)
Profitability	11.711	-3.204	-0.177	18.394	18.709
	(23.909)	(25.143)	(24.939)	(39.614)	(40.104)
Sales Growth	11.153	6.649	7.948	9.515	7.870
	(13.462)	(13.916)	(14.135)	(21.903)	(21.750)
Observations	443	438	438	244	244
R-squared	0.580	0.588	0.592	0.635	0.636
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table 7: The Relation between long-run post-SEO Operating Performance and the Realization of Online Employee Ratings

This table reports the OLS regression results of the effect of online employee ratings on the operating performance of firms after SEOs. The dependent variable *Avg. OIBDA level* is the ratio of operating income before depreciation plus interest income (Compustat item 13 and 62 respectively) to the book value of total assets (item 6) averaged over the three consecutive fiscal years after the SEO. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. OIBDA is ratio of operating income before depreciation plus interest income to the book value of total asset a year before the SEO. Constant (suppressed), firm-headquarter state fixed effects, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables			Avg. OIBDA level		
Overall Rating	0.004				
	(0.017)				
Management Rating		0.042**			
		(0.019)			
Compensation Rating			0.034		
			(0.024)		
Cultural Rating				0.060**	
				(0.028)	
Rating Factor					0.064**
					(0.029)
Ln(Sale)	0.038*	0.037*	0.036*	0.051***	0.049***
	(0.019)	(0.019)	(0.020)	(0.015)	(0.015)
Tobin's Q	0.008	0.004	0.006	0.004	0.001
	(0.014)	(0.014)	(0.013)	(0.011)	(0.011)
Prior Return	0.032*	0.031*	0.032*	-0.024	-0.024
	(0.017)	(0.017)	(0.017)	(0.025)	(0.025)
Ln(Age)	0.028*	0.025*	0.030*	0.076	0.068
	(0.015)	(0.014)	(0.016)	(0.054)	(0.052)
R&D/Sale	-0.017	-0.018	-0.018	-0.051**	-0.054**
	(0.019)	(0.019)	(0.020)	(0.022)	(0.022)
OIBDA	0.464**	0.463**	0.464**	0.284***	0.291***
	(0.225)	(0.220)	(0.227)	(0.103)	(0.100)
Observations	274	272	274	142	142
R-squared	0.775	0.777	0.778	0.837	0.837
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table 8: Years when Anti-SLAPP Legislations were Enacted across U.S. States

SLAPP refers to “strategic lawsuit against public participation.” Many U.S. states have enacted “Anti-SLAPP” laws to protect the exercise of First Amendment Rights of people. These laws provide for early dismissals of meritless SLAPP lawsuits filed against individuals expressing their opinion on a firm or product in a public platform. By 2018, 28 states have enacted Anti-SLAPP laws. In this table, we list the states, which have enacted the Anti-SLAPP laws, and the corresponding years these laws were enacted.

States	**Year of Enactment of Anti SLAPP legislation**
Arizona	2006
Arkansas	2005
California	2005
Connecticut	2017
Delaware	1992
Florida	2000
Georgia	1996
Hawaii	2002
Illinois	2007
Indiana	1998
Kansas	2016
Louisiana	1999
Maine	1995
Maryland	2004
Massachusetts	1994
Missouri	2004
Nebraska	1994
Nevada	1993
New Mexico	2001
New York	2008
Oklahoma	2014
Oregon	2001
Pennsylvania	2000
Rhode Island	1995
Texas	2011
Tennessee	1997
Utah	2001
Vermont	2005

Table 9: The Impact of Anti-SLAPP Laws on the Participation of Reviewers on Glassdoor and on Glassdoor Ratings

This table reports the impact of Anti-SLAPP laws on the participation of reviewers on the Glassdoor website and on the Glassdoor Ratings. The sample consists of all public firm-year observations with coverage on Glassdoor. In Panel A, the dependent variables are *Total # of Reviews* and *# of Normalized Reviews*. *Total # of Reviews* is the number of reviews of a firm in a year given on the Glassdoor website. *# of Normalized Reviews* is the number of reviews of a firm in a year minus the average number of reviews of all firms in the same two-digit SIC code in the same year scaled by the standard deviation of number of reviews of all firms in the same two-digit SIC code in the same year. In Panel B, the dependent variables are the different rating measures. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Anti-SLAPP* is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Profitability* is defined as the ratio of the operating income before depreciation and the book value of assets. *Tangible Asset* is the book value of property, plant, and equipment over the book value of assets. *Tobin's Q* is the ratio of the market value of assets and the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Ln(Asset)* is the natural logarithm of the book value of total assets of a firm. Constant (suppressed), two-digit SIC industry by filing year fixed effects, and firm-headquarter state fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: The Impact of Anti-SLAPP Laws on # of Glassdoor Reviews

	(1)	(2)
Variables	Total # of Reviews	# of Normalized Reviews
Anti-SLAPP	84.278***	0.077***
	(30.296)	(0.013)
Profitability	-658.491***	-0.308***
	(145.314)	(0.112)
Tangible Asset	-141.003	-0.355*
	(174.682)	(0.200)
Tobin's Q	132.242***	0.087***
	(24.478)	(0.017)
Ln(Age)	134.705***	0.098***
	(40.333)	(0.024)
Ln(Size)	405.758***	0.335***
	(42.123)	(0.021)
Observations	15,079	15,079
R-squared	0.318	0.348
State FE	Yes	Yes
Industry X Year FE	Yes	Yes

Panel B: The Impact of Anti-SLAPP Laws on Glassdoor Ratings					
	(1)	(2)	(3)	(4)	(5)
Variables	Overall Rating	Management Rating	Compensation Rating	Cultural Rating	Rating Factor
Anti-SLAPP	-0.034	-0.043	-0.013	-0.297***	-0.211**
	(0.034)	(0.045)	(0.039)	(0.050)	(0.080)
Profitability	0.013	0.044	-0.199***	-0.048	0.053
	(0.063)	(0.058)	(0.056)	(0.081)	(0.109)
Tangible Asset	-0.092*	-0.073	0.165*	-0.160**	-0.127
	(0.052)	(0.074)	(0.089)	(0.069)	(0.091)
Tobin's Q	0.073***	0.084***	0.067***	0.088***	0.103***
	(0.009)	(0.010)	(0.009)	(0.008)	(0.012)
Ln(Age)	0.003	0.002	-0.036**	0.002	-0.007
	(0.012)	(0.012)	(0.015)	(0.018)	(0.019)
Ln(Size)	0.074***	0.057***	0.086***	0.081***	0.098***
	(0.008)	(0.007)	(0.008)	(0.009)	(0.010)
Observations	13,463	13,345	13,356	9,910	9,902
R-squared	0.124	0.101	0.175	0.116	0.127
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table 10: Propensity Score Matching of Firms Located in States with Anti-SLAPP Laws and Firms Located in States without Anti-SLAPP Laws

This table reports the pre- and post-match characteristics of firms located in states with and without Anti-SLAPP laws. We use propensity score matching using the one-to-one "nearest neighbors" methodology with common support. *Treated* and *Control* refers to the firms located in states with and without Anti-SLAPP laws, respectively. We use *Ln(Sale)*, *Ln(Age)*, *Tobin's Q*, *Sales Growth*, and *Profitability* as the six covariates to conduct our matching procedure. Panel A shows the comparison of two groups across the following characteristics: *Ln(Sale)*, *Ln(Age)*, *Tobin's Q*, *Prior Return*, *Sales Growth*, and *Profitability*. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets.

Panel A: Pre-Match Sample Characteristics

	Mean			t-test	
Variable	Treated	Control	%bias	t	p>t
Ln(Sale)	5.30	6.09	-33.30	-4.20	0.00
Ln(Age)	2.43	2.43	0.00	0.00	1.00
Tobin's Q	2.55	2.24	16.20	2.09	0.04
Prior Return	0.29	0.44	-15.40	-2.16	0.03
Sales Growth	0.15	0.16	-2.30	-0.27	0.79
Profitability	-0.16	-0.03	-36.10	-4.44	0.00

Panel B: Post-Match Sample Characteristics

	Mean			t-test	
Variable	Treated	Control	%bias	t	p>t
Ln(Sale)	5.42	5.44	-0.80	-0.13	0.90
Ln(Age)	2.42	2.43	-0.70	-0.13	0.90
Tobin's Q	2.54	2.55	-0.80	-0.13	0.89
Prior Return	0.29	0.27	2.10	0.41	0.68
Sales Growth	0.16	0.15	2.00	0.29	0.78
Profitability	-0.13	-0.11	-4.20	-0.77	0.44

Table 11: Identification Test: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on Announcement Effects of Equity Issues

This table reports the difference-in-difference regression results of the effect of anti-SLAPP laws on announcement returns around SEOs on a propensity score matched sample. The dependent variable *Cumulative Abnormal Return (CAR)* is the three-day cumulative abnormal return centered on the announcement date of SEO, and computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm. The dependent variable *Positive Abnormal Return* is an indicator variable that takes the value 1 if the three-day cumulative abnormal return (CAR) centered on the SEO announcement, computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm, is positive and takes the value 0 if the CAR is non-positive. In Columns (1) and (2), we run a linear regression and logistic regression, respectively. *Anti-SLAPP* is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), two-digit SIC industry by filing year fixed effects, and firm-headquarter state fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Variables	(1) Cumulative Abnormal Return	(2) Positive Abnormal Return (Indicator Variable)
Anti SLAPP	0.063***	0.414***
	(0.021)	(0.144)
Ln(Sale)	0.001	0.004
	(0.005)	(0.022)
Ln(Age)	0.008*	0.052
	(0.004)	(0.034)
Tobin's Q	0.003*	-0.006
	(0.002)	(0.014)
Offer Size	0.000	-0.000
	(0.000)	(0.000)
Sales Growth	0.015	0.068
	(0.010)	(0.052)
R&D/Sale	-0.001	0.005
	(0.004)	(0.018)
Prior Return	-0.005	-0.001
	(0.006)	(0.028)
Profitability	-0.010	-0.024
	(0.014)	(0.055)
Observations	522	450
R-squared/Pseudo R-squared	0.249	0.151
State FE	Yes	Yes
Industry X Year FE	Yes	Yes

Table 12: Identification Test: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on the Propensity to Issue Equity rather than Debt

This table reports the difference-in-differences regression results of the effect of anti-SLAPP laws on debt-equity choices of public firms on a propensity score matched sample. The dependent variable *Equity vs. Debt* is an indicator variable that equals one if equity is issued in the fiscal year, and zero if debt is issued. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by total book assets at the beginning of the fiscal year exceeds 1%. Observations where firms issue both equity and debt in a given fiscal year as well as observations where firms issue neither equity nor debt are dropped. *Anti-SLAPP* is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Profitability* is defined as the ratio of the operating income before depreciation and the book value of assets. *Tangible Asset* is the book value of property, plant, and equipment over the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Ln(Asset)* is the natural logarithm of the book value of total assets of a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. Constant (suppressed), two-digit SIC industry by filing year fixed effects, and firm-headquarter state fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)
Variables	Equity vs. Debt(Indicator Variable)
Anti-SLAPP	0.139***
	(0.044)
Profitability	-0.239**
	(0.105)
Tangible Assets	-0.273***
	(0.069)
Ln(Age)	-0.071***
	(0.021)
Ln(Asset)	-0.064***
	(0.006)
Sales Growth	0.086*
	(0.045)
Prior Return	0.024
	(0.020)
Observations	1,672
Pseudo R-squared	0.443
State FE	Yes
Industry X Year FE	Yes

Table 13: Identification Test: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on the Future Firm Investment Level

This table reports the difference-in-differences regression results of the effect of anti-SLAPP laws on the post-SEO investment level of firms on a propensity score matched sample. The dependent variable *Investment* is the ratio of capital expenditure for a firm in a year scaled by the lagged value of tangible asset of the firm. *Anti-SLAPP* is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), firm-headquarter state fixed effect, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Variables	(1) Investment
Anti SLAPP	0.160**
	(0.075)
Ln(Sale)	-0.015
	(0.020)
Ln(Age)	-0.035**
	(0.016)
Tobin's Q	0.060***
	(0.016)
Offer Size	-0.000
	(0.000)
Sales Growth	0.020
	(0.033)
R&D/Sale	-0.002
	(0.022)
Prior Return	0.062***
	(0.022)
Profitability	0.231**
	(0.105)
Observations	449
R-squared	0.402
State FE	Yes
Industry X Year FE	Yes

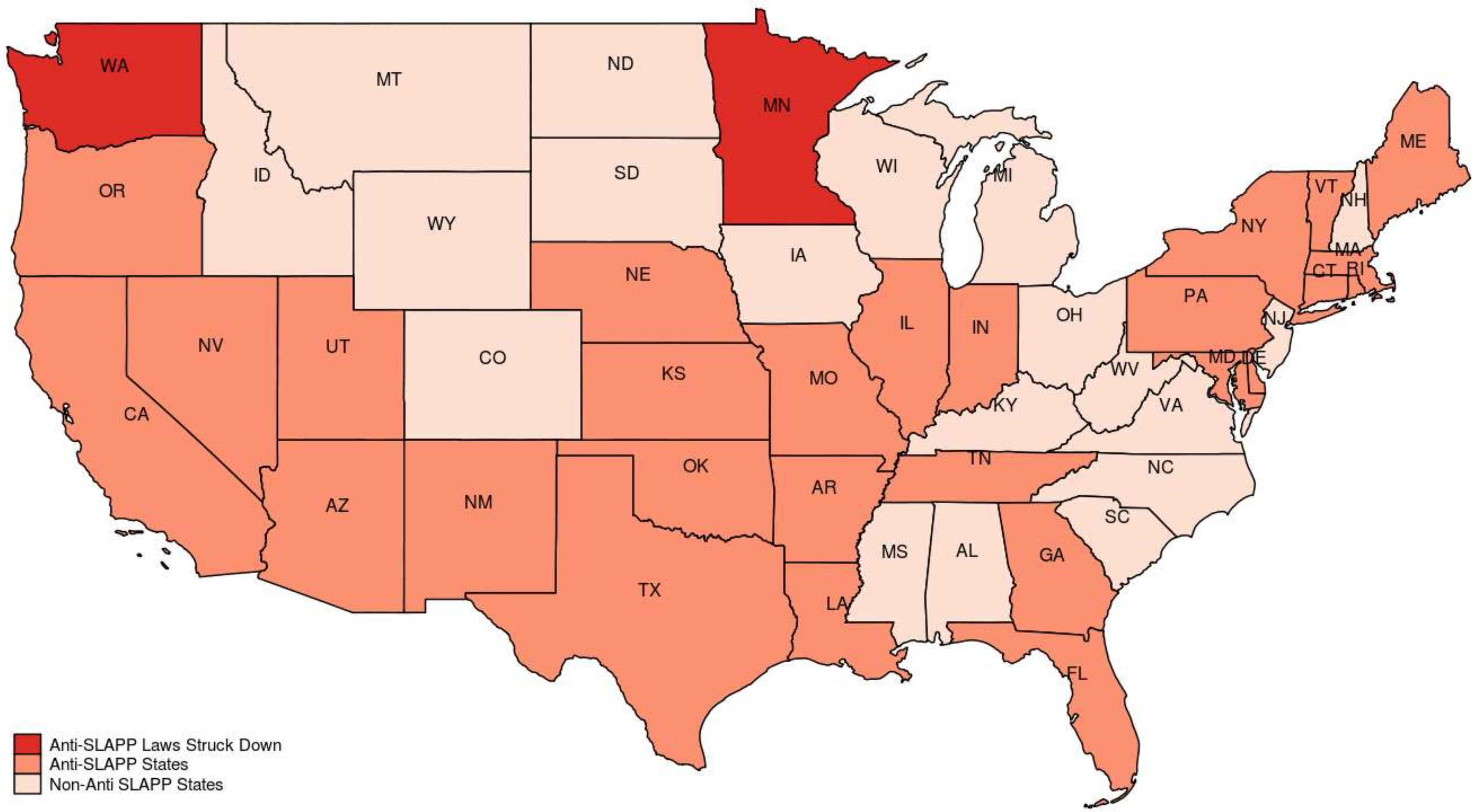
Table 14: Time Trends of the Impact of Anti-SLAPP Laws on Announcement Effects of Equity Issues (Parallel Trend Test)

This table reports the time trend of the effect of anti-SLAPP laws on announcement returns around SEOs on a propensity score matched sample. The dependent variable *Cumulative Abnormal Return (CAR)* is the three-day cumulative abnormal return centered on the announcement date of SEO, and computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm. *T=0* is an indicator variables that is equal to one in the year Anti-SLAPP law is implemented in a firm-headquarter state, otherwise it is equal to zero. *T=+2* is an indicator variable that is equal to one in the years 1 and 2 after the implementation of Anti-SLAPP law in a firm-headquarter state, otherwise it is equal to zero. *T=2+* and onwards is an indicator variable that is equal to one in the year 3 and beyond after the implementation of Anti-SLAPP law in a firm-headquarter state, otherwise it is equal to zero. *T=-4* and *T=-2* are indicator variables that are equal to one in the years 4 and 3 and years 2 and 1, respectively, prior to adoption of Anti-SLAPP law in a firm-headquarter state, otherwise these variables are equal to zero. Our controls include *Ln(Sales)*, *Ln(Age)*, *Offer Size*, *R&D/Sales*, *Profitability*, *Prior Return*, *Tobin's Q, and Sales Growth*. Constant (suppressed), firm-headquarter state fixed effect, and (or) two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)
Variables	Cumulative Abnormal Return
T=-4	0.013
	(0.021)
T=-2	0.038
	(0.030)
T=0	-0.007
	(0.035)
T=+2	0.134***
	(0.037)
T=2+ and onwards	0.094***
	(0.029)
Controls	Yes
Observations	516
R-squared	0.252
State FE	Yes
Industry X Year FE	Yes

Figure 1: US States with and without Anti-SLAPP laws

SLAPP refers to "strategic lawsuit against public participation." These laws protect the exercise of First Amendment Rights of people and provide for early dismissals of meritless SLAPP lawsuits filed against individuals expressing their opinion on a firm or product in a public platform. By 2018, 28 states have enacted Anti-SLAPP laws. In two states, Washington and Minnesota, Anti-SLAPP laws have been struck down by the respective Supreme Courts in 2015 and 2017, respectively. In this figure, we see the map of the states that have enacted the Anti-SLAPP laws, states that have not enacted Anti-SLAPP laws, and the states where Anti-SLAPP laws have been struck down for being unconstitutional.



Appendix

This appendix is divided into six parts. In subsection A1, we explain the intuition behind the sign and magnitude of the SEO announcement effect in our soft information equilibrium in more detail. In subsection A2, we discuss measures taken by Glassdoor to protect the identity of its anonymous reviewers. In subsection A3, we show some robustness tests to support our analysis in the main paper. In section A4, we provide cross-sectional evidence which suggests that the impact of Glassdoor ratings on financial policies of firms become stronger after the staggered passage of anti-SLAPP laws across U.S. states. In section A5, we provide evidence that rules out manipulation of Glassdoor ratings around equity issues of firms. Lastly, in section A6, we show that the local economic or political factors of states do not determine the passage of anti-SLAPP laws across U.S. states. We also have a graph, Figure A1, which shows that the overall ratings for our SEO sample is approximately normally distributed.

A1: The intuition behind the magnitude and sign of the SEO announcement effect in the soft information equilibrium of Chemmanur and Jiao (2005)

We start with discussing the intuition behind the magnitude of announcement effect in the soft information equilibrium.

A1.1: The intuition behind the magnitude of the SEO announcement effect in the soft information equilibrium

We discuss how the magnitude of announcement effect of an equity issue is related to the realization of the soft information signals received by investors upon the announcement of the equity issue (corresponding to point (ii) in the soft information equilibrium discussed in the main paper). To understand the intuition behind the above relation, it is useful to compare the equity issue announcement effect of firms receiving favorable (H) and unfavorable (L) realizations of outsiders' soft information signals in each of the three possible scenarios.

Consider first the scenario of a firm making a high priced equity offering (fraction α_u offered to outsiders) and receiving a negative announcement effect (i.e., where the stock price falls upon announcement). In this case, Chemmanur and Jiao (2005) show that the announcement effect will be less negative (algebraically larger) for firms which received favorable (H) realizations of outsiders' soft information signals than those receiving unfavorable (L) realizations. This is because, while the value of such firms prior to the announcement will be greater than those receiving unfavorable realizations of soft information (recall that firms receiving H realizations are more likely to be type G firms, so that outsiders will set the probability of such firms being of type G to be larger), their value subsequent to the announcement will also be greater, so that we can show that the drop in share price for such firms will be smaller than for those receiving unfavorable realizations of outsiders' soft information signals.

Consider now the second scenario, where the firm makes a high priced equity offering, but its announcement effect is positive (i.e., share price increases upon announcement). In this scenario, the increase in share price for a firm which receives a good realization of outsiders' soft information signals may be either larger or smaller than one which received a bad realization of outsiders' soft information signals (while the level of equity prices subsequent to the announcement will always be higher for the former, the share price increase may be greater for the latter firms in some cases, since the latter firms are valued lower than the former before the equity issue announcement).

Consider now the third scenario, where the firm makes a low priced equity offering (revealing itself to be of type B), so that the announcement effect is always negative. In this case, the announcement effect for firms for which outsiders received a favorable (H) realization of their soft information signals will always be more negative (algebraically smaller) than that for firms receiving unfavorable (L) realizations (since the share price is dropping from a lower level for firms in the latter situation). However, since the effect of the first scenario dominates that of the other two scenarios, Chemmanur and Jiao (2005) show that the average announcement effect will always be algebraically larger (i.e., will be more positive, or less negative) for firms receiving more favorable realizations of their soft information signals.

Next, we discuss the intuition behind the sign of announcement effect in the soft information equilibrium.

A1.2: The intuition behind the sign of the SEO announcement effect in the soft information equilibrium

We now discuss how the sign of announcement effect (positive or negative) of an equity issue is related to the realization of the soft information signals received by investors upon the announcement of the equity issue (corresponding to point (iii) in the soft information equilibrium discussed in the main paper). In order to explain the intuition behind the above it is useful to consider the two possible cases covered by the soft information equilibrium: the scenario when the type B mimics the type G by setting a high price for its equity, and the scenario where the type B separates itself by setting a low price.

Let us consider the high price scenario first. Before the announcement of the equity issue, all three types of firms are pooled together conditional on the soft information signals outsiders receive about them. Thus the value of the equity of a firm before its equity issue announcement is a weighted average of the intrinsic equity values of type G, type M, and type B firms. Since, in the scenario where the type B mimics the type G, only type G and type B firms issue equity at the high price (type G with probability 1, and type B with probability y $<$ 1), the equity value after the announcement will be a weighted average of the intrinsic values of only the type G and type B firms. When the soft information signal available to outsiders is precise enough, and the net present value of the firm's new project d is large enough, the type B firm mimics the type G firm less often by setting a high price (i.e., y is small), since the cost to a type B firm arriving from outside investors rejecting its equity issue is large (foregone NPV d) and the type B firm knows that potential investors who have access to very precise soft information will reject the type B firm's high price equity offering with a high probability. This means that the price after the announcement of an equity issue will be larger than the price before the announcement, since equity market investors will place a high probability weight on the firm making the equity issue being a type G. In other words, the announcement effect to the equity issue will be positive in this scenario.

Consider now the low price scenario where the type B issues equity at a low price. In this scenario the issuing firm will be revealed as a type B firm with probability 1, so that the announcement effect in this case will always be negative. Given the above two scenarios, if the outsiders' soft information signals are sufficiently precise, and the proportion of type G firms (relative to the proportion of type B) is significant, the average announcement effect across firms making equity issues will be positive as well.

Let us now consider the case where the the outsiders' soft information signals are not precise enough, or the new project net present value d is not large enough. In this case, the type B firm will mimic the type G more often (y will be larger), so that the announcement effect to a firm making even a high priced equity offering will be negative. This is because, in this case, outside investors will place a higher probability weight on a firm making a high price equity offering being a type B firm, so that the stock price upon equity issue announcement (probability-weighted average of the intrinsic value of the type G and type B firms) will be lower than the stock price prior to equity issue announcement (probability-weighted average of the intrinsic values of all three types of firms). Since (as discussed above) the announcement effect to a firm making a low priced equity offering is always negative, the average announcement effect across all equity issues will then be negative as well.

A2: Measures taken by the Glassdoor to protect the Identity of its Anonymous Reviewers

Glassdoor takes several steps to protect the identity of its anonymous reviewers, including filing lawsuits on their behalf.[1] Here is an excerpt from their website:

"In appropriate circumstances, we've funded the filing of anti-SLAPP motions on behalf of our users to further protect workers' ability to post anonymous reviews. Anti-SLAPP statutes, in those states that have them, typically provide for early dismissal of the lawsuit and recovery of attorney's fees unless the plaintiff can show a likelihood of prevailing in their action."

"In addition, if we find that an employer has presented false evidence in a sworn declaration in support of legal action to obtain user identity from Glassdoor, we reserve the right to pursue legal action against that employer for perjury and may fund the defense of the affected user in the underlying lawsuit. While we can't offer these additional legal protections to every user subject to legal action for anonymous speech on Glassdoor, we believe that by taking this stand in even a small number of cases, we can deter the filing of meritless lawsuits against our users."

[1] Please refer this link for a detailed description of these steps: (https://help.glassdoor.com/article/What-else-does-Glassdoor-do-to-protect-and-defend-the-anonymous-free-speech-of-its-users/en_US)

A3: Robustness Tests

In this section, we conduct some additional empirical tests to support our analyses in the main paper. We provide evidence, which support our baseline analyses and identification strategy.

A3.1: The Relation between the Probability of a Positive Announcement Effect and the Realization of Online Employee Ratings: Linear Probability Model)

In the main paper, we show that firms with higher Glassdoor ratings are associated with greater probability of positive announcement effect using a logistic regression. In Table A1, we show that our results are robust to using a linear probability model rather than a logistic regression model. In Columns (1), (2), (4), and (5), we show that the coefficients of overall rating, management rating, cultural rating, and the common rating factor are positive and significant at the 1 percent, 5 percent, 10 percent, and 5 percent levels, respectively. These results suggest that firms with better online employee ratings have higher probability of positive SEO announcement returns, which supports our hypothesis **H2**.

A3.2: The Relation between the Propensity to Issue Equity rather than Debt and the Realization of Online Employee Ratings: Linear Probability Model

In the main paper, we show that firms with higher Glassdoor ratings are associated with greater propensity to issue equity rather than debt using a logistic regression. In Table A2, we show that our results are robust to using a linear probability model rather than a logistic regression model. In Columns (1), (3), (4), and (5), we show that the coefficients of overall rating, compensation rating, cultural rating, and the common rating factor are positive and significant at the 10 percent, 5 percent, 10 percent, and 10 percent levels, respectively. These results suggest that firms with better online employee ratings are associated with greater preference of issuing equity over debt, which supports our hypothesis **H3**

A3.3: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on Announcement Effects of Equity Issues (Unmatched Sample)

In the main paper, we conduct our DID analysis using a propensity-matched sample of treated firms (headquartered in states with anti-SLAPP laws) and controls firms (headquartered in states without anti-SLAPP laws). Our results are robust to conduction our DID analysis over the entire sample. In Table A3, we show that the passage of anti-SLAPP laws lead to higher announcement effect and greater probability of positive announcement effect. In Columns (1) and (2), we run a linear regression and logistic regression, respectively, over the entire unmatched sample. We show that the passage of anti-SLAPP laws lead to higher SEO announcement returns (positive and significant at 10% level) and greater probability of positive announcement returns (positive and significant at 10% level). These results suggest that information content in online employee ratings is greater for firms after anti-SLAPP laws are implemented in firm-headquarter states and these firms, in turn, have higher SEO announcement returns and greater probability of positive announcement returns, which supports our hypotheses **H1** and **H2**, respectively.

A3.4: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on the Propensity to Issue Equity rather than Debt (Unmatched Sample)

In this section, we conduct our DID analysis over the entire unmatched sample and show that our results are similar to DID analysis conducting using a propensity-matched sample. In Table A4, we show that the passage of anti-SLAPP laws lead to greater propensity of issuing equity rather than debt. In Column (1), we show that the coefficients of anti-SLAPP indicator indicator is positive and significant at 1 percent level. This results suggest that information content in online employee ratings is greater for firms after anti-SLAPP laws are implemented in firm-headquarter states and these firms, in turn, have greater probability of issuing equity rather than debt, which supports our hypothesis **H3**.

A3.5: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on the Future Firm Investment level (Unmatched Sample)

In this section, we conduct our DID analysis over the entire unmatched sample and show that our results are similar to DID analysis conducting using a propensity-matched sample. In Table A5, we show that the passage of anti-SLAPP laws lead to greater level of investment by firms after SEOs. In Column (1), we show that the coefficients of anti-SLAPP indicator indicator is positive and significant at 5 percent level. This results suggest that information content in online employee ratings is greater for firms after anti-SLAPP laws are implemented in firm-headquarter states. This in turn, lowers the cost of equity for firms, i.e., higher SEO announcement effect (as we show in Table A3). Consequently, some projects which were earlier negative NPV may become positive NPV for above firms (due to lower cost of capital, and these firms, in turn, have higher future investment level, which supports our hypothesis **H4**.

A4: The Impact of Glassdoor Ratings on External Financial Policies of Firms: Cross-sectional Analysis)

In this section, we provide some cross-sectional evidence which provide additional evidence that Glasdoor ratings affect external financial policies of firms. Specifically, we show the impact of Glassdoor ratings on announcement effect and equity versus debt issues are stronger after the passage of anti-SLAPP laws across states. We show this using the following empirical specification:

$$Outcome_{i,t} = \alpha Anti\text{-}SLAPP_{i,t} + \ \beta Anti\text{-}SLAPP_{i,t} \times Ratings_{i,t} + \gamma Ratings_{i,t} + X_{i,t} + \epsilon_{i,t}, \qquad (1)$$

where i indexes firm, s indexes firm-headquarter state, and t indexes year. *Outcome* refers to the following dependant variables, namely, announcement returns, probability of positive announcement returns, and equity versus debt issues by firms. *Anti-SLAPP* is an indicator variable, which takes the value 1 if the firm-headquarter state have anti-SLAPP laws in that year and takes the value 0, otherwise. *Ratings* proxies for measures of Glassdoor ratings: the four rating measures and the common rating factor. We expect that β, the coefficient of interaction of anti-SLAPP indicator and Glassdoor ratings to be positive. This is because the information content of Glassdoor ratings will be greater after the passage of anti-SLAPP laws as we discussed in our main paper.

In Table A6, we provide empirical evidence in support of the above argument. In Column (1) of Panel A, we show that upon regressing cumulative abnormal return (CAR) on the interaction of common rating factor and anti-SLAPP indicator and other controls, the coefficient of interaction term is positive and significant (10% level). In Column (2) of Panel A, we run a linear probability regression, where the dependent variable takes the value one if announcement return is positive, otherwise the indicator variable is equal to zero. We show that the coefficient of the interaction of common rating factor and anti-SLAPP indicator is positive and significant (1% level). We have the same set of controls used in our analysis in the main paper. In Panel B, we show the cross-sectional impact of Glassdoor ratings on equity versus debt issues using a linear probability model. The dependent variable takes the value one if equity is issued and takes the value zero if debt is issued. We show that the coefficient of the interaction of common rating factor and anti-SLAPP indicator is positive and significant (10% level).[2] We use a propensity score matched sample for our above analysis. Our results are robust to using the entire unmatched sample.

The above analysis provides additional evidence that the staggered passage of anti-SLAPP laws across U.S. states make Glassdoor ratings more informative for investors, leading to bigger impact on announcement effect of equity issues and on equity versus debt issues by firms. In other words, the same level of Glassdoor rating will have bigger impact on firms' external financing after the passage of anti-SLAPP laws. Thus, the above results show that the anti-SLAPP laws affect the announcement effect of equity issues and equity versus debt issues through the Glassdoor ratings channel.

A5: Time Trends Analysis of the Glassdoor Ratings around the Announcement of an Equity Issue (Test of Manipulation of Glassdoor Ratings)

In this section, we provide evidence which rules out manipulation of Glassdoor ratings around equity issues by firms. It is possible that firms may inflate their Glassdoor ratings prior to equity issue by encouraging their employees to provide favorable review on Glassdoor, which may lead to favorable perception of firms among investors. If there is manipulation of ratings, we would expect firms to have positive jumps in rating before their equity issues. We conduct a time-trend analysis

[2] Due to lack of space we do not report the interaction terms involving other Glassdoor rating measures and anti-SLAPP indicator. Our results are similar when we use interaction terms with other Glassdoor rating measures.

of Glassdoor ratings of firms around their equity issues. Our sample is a firm-year panel including all firms with Glassdoor ratings that have issued equity between 2008 and 2017. In Table A7, we regress our five Glassdoor rating measures, four rating variables and one common rating factor, on time trends (pre- and post-SEO) and other controls. We include yearly time trends from two years prior to equity issues to two years post equity issues. We use the following indicator variables to capture time trends: *T=-2*, *T=-1*, *T=0*, *T=+1*, and *T=+2*. *T=0* is an indicator variable that is equal to one in the year in which a firm issues equity, otherwise it takes the value zero, while *T=-1* and *T=-2* are indicator variables that are equal to one in the years 1 and 2, respectively, prior to the equity issue, otherwise they are equal to zero. *T=+1* and *T=+2* are indicator variables that are equal to one in the years 1 and 2, respectively, after the equity issue, otherwise they are equal to zero. We control for firm size, asset tangibility age, Tobin's Q, and profitability. We find that almost all coefficients of the time trend variables are insignificant. In particular, the coefficients of indicator variables prior to equity issues are insignificant. In case of manipulation, we would expect firms to experience jump in ratings prior to equity issues. The above empirical evidence rules out manipulation of ratings by firms, on average, prior to their equity issues.

A6: The determinants of Anti-SLAPP Laws (Local Economic or Political Factors of States do not Matter)

In this section, we check whether local economic or political factors of states affect the passage of anti-SLAPP laws across those states. We find that local economic or political factors do not determine the passage of anti-SLAPP laws in states. We use a linear probability model where the dependent variable takes the value one in a year if a state passes anti-SLAPP law in that year.[3] Our sample consists of all state-year observations from 1981 to 2017. We drop observations of a particular state after the passage of anti-SLAPP laws in that state. Our independent variables, local economic or political factors, are lagged by one period. We use the annual growth rate of state GDP, the natural logarithm of state population (annual), the natural logarithm of states' per capita GDP (annual), the unemployment rates of states (annual), and indicator variables for Democratic or Republican partisan control, i.e., control of legislative chambers and governorship, as controls for states' economic and political factors. We obtain annual data on growth rate of state GDP,

[3] Our results are robust to using a logistic regression model.

state population, states' per capita GDP, and the state-level unemployment rate from the Bureau of Economic Analysis (BEA). We obtain data on political control from the website of National Conference of State Legislatures. We show in Table A8, none of these factors are significant in predicting the passage of anti-SLAPP laws. In Column (1) our regression include year fixed effects, while in Column (2), our regression includes both year and state fixed effects. In both of the above specifications, we find that passage of anti-SLAPP laws are exogenous to local economic or political factors that may affect firms' financial or real activities. This test supports the validity of using the staggered passage of anti-SLAPP laws across U.S. states as an appropriate exogenous shock for our empirical analysis.

References

Chemmanur, Thomas, and Yawen Jiao, 2005, Seasoned Equity Issues with "Soft" Information: Theory and Empirical Evidence, Working Paper, Boston College.

Table A1: The Relation between the Probability of a Positive Announcement Effect and the Realization of Online Employee Ratings: Linear Probability Model

This table reports the linear probability model (LPM) regression results of the effect of online employee ratings on the probability of positive abnormal announcement returns around SEOs. The dependent variable Positive Abnormal Return takes the value 1 if the three-day cumulative abnormal return (CAR) centered on the SEO announcement, computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm, is positive and takes the value 0 if the CAR is non-positive. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), firm-headquarter state fixed effects, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables	Positive Abnormal Return (Indicator Variable)				
Overall Rating	0.068***				
	(0.026)				
Management Rating		0.057**			
		(0.023)			
Compensation Rating			0.011		
			(0.034)		
Cultural Rating				0.059*	
				(0.033)	
Rating Factor					0.076**
					(0.033)
Ln(Sale)	0.006	0.011	0.013	0.016	0.013
	(0.020)	(0.021)	(0.021)	(0.030)	(0.030)
Ln(Age)	0.052	0.048	0.048	0.047	0.054
	(0.035)	(0.035)	(0.035)	(0.068)	(0.067)
Tobin's Q	-0.023*	-0.024*	-0.016	-0.028	-0.033
	(0.014)	(0.014)	(0.014)	(0.023)	(0.022)
Offer Size	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	0.029	0.024	0.033	0.061	0.051
	(0.064)	(0.065)	(0.064)	(0.079)	(0.080)
R&D/Sale	-0.004	0.001	0.004	0.000	-0.006
	(0.019)	(0.021)	(0.021)	(0.033)	(0.033)
Prior Return	0.006	0.006	0.011	-0.009	-0.011
	(0.036)	(0.036)	(0.036)	(0.052)	(0.052)
Profitability	-0.030	-0.063	-0.046	-0.167	-0.178
	(0.107)	(0.115)	(0.112)	(0.129)	(0.127)
Observations	538	532	532	303	303
R-squared	0.292	0.283	0.275	0.305	0.309
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table A2: The Relation between the Propensity to Issue Equity rather than Debt and the Realization of Online Employee Ratings: Linear Probability Model

This table reports the linear probability model regression results of the effect of online employee ratings on debt versus equity issues of public firms. The dependent variable *Equity vs. Debt* equals one if equity is issued in the fiscal year, and zero if debt is issued. Observations where firms issue both equity and debt in a given fiscal year as well as observations where firms issue neither equity nor debt are dropped. *Overall Rating* is the average of overall rating in each year for each firm over a period of 365 days prior to the reporting of annual 10-K report. Similarly, *Management Rating* is the average of senior management rating; *Compensation Rating* is the average of compensation and benefits rating; and *Cultural Rating* is the average of culture and values rating, in each year for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *Profitability* is defined as the ratio of the operating income before depreciation and the book value of assets. *Tangible Asset* is the book value of property, plant, and equipment over the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Ln(Asset)* is the natural logarithm of the book value of total assets of a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. Constant (suppressed), firm-headquarter state fixed effects, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables	Equity vs Debt (Indicator Variable)				
Overall Rating	0.020*				
	(0.011)				
Management Rating		0.016			
		(0.011)			
Compensation Rating			0.031**		
			(0.013)		
Cultural Rating				0.019*	
				(0.010)	
Rating Factor					0.018*
					(0.010)
Profitability	-0.328***	-0.337***	-0.333***	-0.391***	-0.392***
	(0.069)	(0.070)	(0.069)	(0.078)	(0.077)
Tangible Assets	-0.331***	-0.327***	-0.335***	-0.366***	-0.366***
	(0.062)	(0.064)	(0.063)	(0.068)	(0.067)
Ln(Age)	-0.055***	-0.056***	-0.054***	-0.050***	-0.050***
	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)
Ln(Asset)	-0.067***	-0.066***	-0.067***	-0.063***	-0.063***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Sales Growth	0.069	0.069	0.065	0.055	0.055
	(0.043)	(0.044)	(0.044)	(0.046)	(0.046)
Prior Return	0.047**	0.044*	0.046**	0.058**	0.056**
	(0.022)	(0.023)	(0.022)	(0.026)	(0.026)
Observations	2,212	2,197	2,197	1,694	1,693
R-squared	0.510	0.508	0.509	0.499	0.499
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table A3: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on Announcement Effects of Equity Issues (Unmatched Sample)

This table reports the difference-in-differences regression results of the effect of anti-SLAPP laws on announcement returns around SEOs on the entire (unmatched) sample. The dependent variable *Cumulative Abnormal Return (CAR)* is the three-day cumulative abnormal return centered on the announcement date of SEO, and computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm. The dependent variable *Positive Abnormal Return* takes the value 1 if the three-day cumulative abnormal return (CAR) centered on the SEO announcement, computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm, is positive and takes the value 0 if the CAR is non positive. In Columns (1) and (2), we run a linear regression and logistic regression, respectively. Anti-SLAPP is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), two-digit SIC industry by filing year fixed effects, and firm-headquarter state fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)
Variables	Cumulative Abnormal Return	Positive Abnormal Return(Indicator Variable)
Anti SLAPP	0.046*	0.282*
	(0.023)	(0.159)
Ln(Sale)	0.003	0.003
	(0.004)	(0.018)
Ln(Age)	0.009*	0.061*
	(0.005)	(0.032)
Tobin's Q	0.003**	-0.009
	(0.002)	(0.014)
Offer Size	0.000	-0.000
	(0.000)	(0.000)
Sales Growth	0.013	0.057
	(0.010)	(0.047)
R&D/Sale	-0.002	-0.001
	(0.005)	(0.014)
Prior Return	-0.005	0.004
	(0.006)	(0.022)
Profitability	-0.013	-0.027
	(0.013)	(0.051)
Observations	578	498
R-squared/Pseudo R-squared	0.237	0.148
State FE	Yes	Yes
Industry X Year FE	Yes	Yes

Table A4: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on the Propensity to Issue Equity rather than Debt (Unmatched Sample)

This table reports the difference-in-differences regression results of the effect of anti-SLAPP laws on debt-equity choices of public firms on the entire (unmatched) sample. The dependent variable *Equity vs. Debt* equals one if equity is issued in the fiscal year, and zero if debt is issued. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by total book assets at the beginning of the fiscal year exceeds 1%. Observations where firms issue both equity and debt in a given fiscal year as well as observations where firms issue neither equity nor debt are dropped. Anti-SLAPP is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Profitability* is defined as the ratio of the operating income before depreciation and the book value of assets. *Tangible Asset* is the book value of property, plant, and equipment over the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Ln(Asset)* is the natural logarithm of the book value of total assets of a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. Constant (suppressed), two-digit SIC industry by filing year fixed effects, and firm-headquarter state fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)
Variables	Equity vs. Debt
Anti-SLAPP	0.056**
	(0.026)
Profitability	-0.234**
	(0.105)
Tangible Assets	-0.208***
	(0.065)
Ln(Age)	-0.066***
	(0.020)
Ln(Asset)	-0.064***
	(0.006)
Sales Growth	0.094**
	(0.039)
Prior Return	0.027
	(0.017)
Observations	1,898
Pseudo R-squared	0.439
State FE	Yes
Industry X Year FE	Yes

Table A5: Difference-in-Differences Analysis of the Impact of Anti-SLAPP Laws on the Future Firm Investment Level (Unmatched Sample)

This table reports the difference-in-differences regression results of the effect of anti-SLAPP laws on the post-SEO investment level of firms on the entire (unmatched) sample. The dependent variable *Investment* is the ratio of capital expenditure for a firm in a year scaled by the lagged value of tangible asset of the firm. Anti-SLAPP is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), firm-headquarter state fixed effect, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)
Variables	Investment
Anti SLAPP	0.204**
	(0.077)
Ln(Sale)	-0.007
	(0.019)
Ln(Age)	-0.028*
	(0.016)
Tobin's Q	0.062***
	(0.015)
Offer Size	-0.000
	(0.000)
Sales Growth	0.026
	(0.030)
R&D/Sale	0.005
	(0.022)
Prior Return	0.054**
	(0.023)
Profitability	0.249**
	(0.105)
Observations	495
R-squared	0.389
State FE	Yes
Industry X Year FE	Yes

Table A6: Cross-sectional variation in the Impact of Glassdoor Ratings on Announcement Effects of Equity Issues and on the Propensity to Issue Equity rather than Debt

This table reports the cross-sectional regression results of the effect of interaction of Anti-SLAPP laws with Glassdoor ratings on announcement returns around SEOs and on debt-equity choices of public firms. Panel A shows the cross-sectional impact of Anti-SLAPP laws on announcement returns while Panel B shows the impact on equity versus debt issues. In Panel A, the dependent variable *Cumulative Abnormal Return (CAR)* is the three-day cumulative abnormal return centered on the announcement date of SEO, and computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm. The dependent variable *Positive Abnormal Return* takes the value 1 if the three-day cumulative abnormal return (CAR) centered on the SEO announcement, computed by subtracting value-weighted CRSP market return from the raw return of the issuing firm, is positive and takes the value 0 if the CAR is non positive. In Columns (1) and (2), we run a linear regression and logistic regression, respectively. *Anti-SLAPP* is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Ln(Sale)* is the natural logarithm of sales made by a firm in a fiscal year. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Offer Size* is defined as the product of offer price and number of shares offered by a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *R&D/Sales* is defined as the ratio of R&D expenditure of a firm in a year scaled by its sales in that year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. *Profitability* is defined as the ratio of operating income before depreciation and the book value of assets. Constant (suppressed), two-digit SIC industry by filing year fixed effects, and firm-headquarter state fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively. In Panel B, the dependent variable *Equity vs. Debt* equals one if equity is issued in the fiscal year, and zero if debt is issued. A firm is considered to have raised equity (debt) when the net equity (debt) issued divided by total book assets at the beginning of the fiscal year exceeds 1%. Observations where firms issue both equity and debt in a given fiscal year as well as observations where firms issue neither equity nor debt are dropped. Anti-SLAPP is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. *Profitability* is defined as the ratio of the operating income before depreciation and the book value of assets. *Tangible Asset* is the book value of property, plant, and equipment over the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Ln(Asset)* is the natural logarithm of the book value of total assets of a firm. *Sales Growth* is defined as ratio of change in sales in the current year minus the sales in the previous year scaled by the sales in previous year. *Prior Return* is the compounded daily stock returns over the past 12-month period prior to the SEO. Constant (suppressed), two-digit SIC industry by filing year fixed effects, and firm-headquarter state fixed effects are included in all regressions. All standard errors are clustered at the firm-headquarter state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Anti-SLAPP laws and Announcement Effect (Interaction tests)		
	(1)	(2)
Variables	Cumulative Abnormal Return	Positive Abnormal Return (Indicator Variable)
Rating Factor X Anti-SLAPP	0.030*	0.145***
	(0.016)	(0.052)
Rating Factor	-0.005	-0.049
	(0.011)	(0.049)
Ln(Sale)	0.004	0.012
	(0.006)	(0.033)
Ln(Age)	0.003	0.034
	(0.012)	(0.075)
Tobin's Q	-0.006	-0.052**
	(0.005)	(0.023)
Offer Size	0.000	0.000
	(0.000)	(0.000)
Sales Growth	0.009	0.082
	(0.025)	(0.115)
R&D/Sale	0.002	-0.003
	(0.007)	(0.019)
Prior Return	-0.005	-0.006
	(0.015)	(0.038)
Profitability	-0.047**	-0.251*
	(0.018)	(0.137)
Observations	276	276
R-squared	0.282	0.338
State FE	Yes	Yes
Industry X Year FE	Yes	Yes

Panel B: Anti-SLAPP laws and Equity vs. Debt Issues (Interaction Tests)	
Variables	(1) Equity vs. Debt
Rating Factor X Anti-SLAPP	0.033*
	(0.017)
Anti-SLAPP	0.051
	(0.084)
Rating Factor	-0.020
	(0.016)
Profitability	-0.458***
	(0.089)
Tangible Assets	-0.405***
	(0.083)
Ln(Age)	-0.053
	(0.032)
Ln(Asset)	-0.059***
	(0.008)
Sales Growth	0.014
	(0.040)
Prior Return	0.067***
	(0.017)
Observations	1,354
R-squared	0.522
State FE	Yes
Industry X Year FE	Yes

Table A7: Time Trends Analysis of the Glassdoor Ratings around Announcement of Equity Issues (Test of Manipulation of Glassdoor Ratings)

This table reports the time trend results of the Glassdoor ratings around announcements of equity issues to check for manipulation of Glassdoor ratings around equity issues. The dependent variables are the different Glassdoor rating measures. *Overall Rating* is the average of overall star rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO. Similarly, *Management Rating* is the average of senior management rating (on a scale of 1 to 5); *Compensation Rating* is the average of compensation and benefits rating (on a scale of 1 to 5); and *Cultural Rating* is the average of culture and values rating (on a scale of 1 to 5), for each firm, calculated in the same manner. *Rating Factor* is the first factor obtained from factor analysis using the above-mentioned four employee rating measures on Glassdoor. *T=0* is an indicator variable that is equal to one in the year in which a firm issues equity, otherwise it takes the value zero, while *T=-1* and *T=-2* are indicator variables that are equal to one in the years 1 and 2, respectively, prior to the equity issue, otherwise they are equal to zero. *T=+1* and *T=+2* are indicator variables that are equal to one in the years 1 and 2, respectively, after the equity issue, otherwise they are equal to zero. *Profitability* is defined as the ratio of the operating income before depreciation and the book value of assets. *Tangible Asset* is the book value of property, plant, and equipment over the book value of assets. *Tobin's Q* is the ratio of market value of assets and the book value of assets. *Ln(Age)* is defined as the natural logarithm of one plus the number of years a firm has return data available from CRSP database. *Ln(Asset)* is the natural logarithm of the book value of total assets of a firm. Constant (suppressed), firm-headquarter state fixed effect, and two-digit SIC industry by filing year fixed effects are included in all regressions. All standard errors are clustered at the industry by filing year level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables	Overall Rating	Management Rating	Compensation Rating	Cultural Rating	Rating Factor
T=-2	0.010	0.050	0.064	0.072	0.066
	(0.056)	(0.073)	(0.063)	(0.066)	(0.081)
T=-1	-0.024	-0.058	-0.108	-0.106	-0.072
	(0.076)	(0.084)	(0.085)	(0.079)	(0.098)
T=0	0.034	0.092**	0.024	0.112**	0.090
	(0.041)	(0.041)	(0.038)	(0.055)	(0.061)
T=+1	0.104	0.184*	0.013	0.132	0.114
	(0.097)	(0.099)	(0.081)	(0.175)	(0.216)
T=+2	0.124	0.117	0.085	0.343***	0.458***
	(0.082)	(0.082)	(0.061)	(0.110)	(0.143)
Profitability	-0.204**	-0.098	-0.349***	-0.150	-0.077
	(0.097)	(0.101)	(0.080)	(0.106)	(0.130)
Tangible Assets	-0.164*	-0.299***	0.103	-0.250**	-0.330**
	(0.087)	(0.103)	(0.086)	(0.119)	(0.135)
Market to Book	0.060***	0.069***	0.059***	0.072***	0.091***
	(0.012)	(0.014)	(0.010)	(0.013)	(0.016)
Ln(Age)	-0.015	-0.031*	-0.050***	0.004	-0.004
	(0.019)	(0.018)	(0.017)	(0.025)	(0.031)
Ln(Asset)	0.079***	0.073***	0.088***	0.075***	0.099***
	(0.010)	(0.012)	(0.010)	(0.014)	(0.017)
Observations	3,457	3,419	3,421	2,322	2,319
R-squared	0.187	0.175	0.262	0.198	0.218
State FE	Yes	Yes	Yes	Yes	Yes
Industry X Year FE	Yes	Yes	Yes	Yes	Yes

Table A8: Determinants of Anti-SLAPP Laws

This table reports the impact of state-level economic and political factors on passage of Anti-SLAPP laws using a linear probability model. *Anti-SLAPP* is an indicator variable, which takes the value 1 if a firm is headquartered in a state in a given year having anti-SLAPP laws in that year and takes the value 0, otherwise. The sample consists of state-year observations from 1981 to 2017. State-year observations after the passage of Anti-SLAPP laws are excluded. *State GDP growth rate* is the annual growth rate of gross domestic products of a state. *Ln(State Population)* is the natural logarithm of population of a state in a year. *Ln(State Per Capital Income)* is the natural logarithm of the per capital income of a state in a year. *State Unemployment rate* is the annual unemployment rate in a state. *Democratic State control* is an indicator variable that takes the value one if the Democratic Party controls both the legislative chambers and the governorship. *Republican State control* is an indicator variable that takes the value one if the Republican Party controls both the legislative chambers and the governorship. Constant (suppressed), year, and (or) state fixed effects are included in the regressions. All standard errors are clustered at the state level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)
Variables	Anti-SLAPP	Anti-SLAPP
State GDP growth rate	0.001	0.000
	(0.001)	(0.001)
Ln(State Population)	0.002	0.107
	(0.004)	(0.079)
Ln(State Per Capital Income)	0.020	0.064
	(0.023)	(0.087)
State Unemployment rate	-0.001	0.002
	(0.002)	(0.003)
Democratic State Control	0.013	0.013
	(0.008)	(0.011)
Republican State Control	0.002	0.015
	(0.009)	(0.012)
Observations	1,478	1,478
R-squared	0.032	0.081
State FE	No	Yes
Year FE	Yes	Yes

Figure 1: Histogram of Online Employee Ratings

This figure presents the histogram of *Overall Rating* in employee reviews for SEOs. The curve shows the normal distribution. *Overall Rating* is the average of overall rating (on a scale of 1 to 5) for each firm over a period of 365 days prior to the announcement of its SEO.