Three Essays in Entrepreneurial and Corporate Finance

Author: Qianqian Yu

Boston College Electronic Thesis or Dissertation, 2017

Boston College

Wallace E. Carroll Graduate School of Management

Department of Finance

THREE ESSAYS IN ENTREPRENEURIAL AND CORPORATE FINANCE

a dissertation by

QIANQIAN YU

submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Finance

April 2017

Acknowledgements

First and foremost, I would like to express my respect and gratitude to the faculty, staff, and my fellow graduate students at Boston College who have extended their warmest support to me during my doctoral study. In particular, I am deeply thankful to my dissertation committee chair, Thomas Chemmanur, for his great advice, guidance, encouragement, and support throughout my dissertation research. His enthusiasm for research and hardworking attitude always inspired me. I could not have asked for a better advisor and mentor for my doctoral study. I have also benefited tremendously from many conversations with another member of my dissertation committee, Philip Strahan. I am also deeply indebted to the other members of my dissertation committee: Alan Marcus, Robert Taggart, and Hassan Tehranian. I would also like to thank my coauthor, Karthik Krishnan, for his help and encouragement throughout my dissertation research.

Finally, on a personal note, I would like to express my deep thanks to my family for their support and love throughout my doctoral study and my life in general.

Table of Contents

THREE ESSAYS IN ENTREPRENEURIAL AND CORPORATE FINANCE

by

Qianqian Yu

Department of Finance, Boston College

Dissertation Committee:

Professor Thomas Chemmanur (Chair)

Professor Alan Marcus

Professor Philip Strahan

Professor Robert Taggart

Professor Hassan Tehranian

Abstract

My dissertation is comprised of three chapters. In the first chapter, I analyze the effect of top management changes on subsequent corporate innovation in venture capital-backed private firms using a hand-collected dataset. I find that top management changes are associated with significantly more and higher quality corporate innovation (as measured by their patenting activity). I show that top management changes are likely to be venture-driven and that the effect of top management changes on corporate innovation is stronger for firms where venture capitalists have greater power. An instrumental variable analysis using an exogenous shock to the supply of outside managers available for hire implies a causal effect of top management changes on corporate innovation. I establish that one mechanism through which top management changes enhance corporate innovation is through new management teams hiring more inventors for a given investment size. I also show that both top management changes and corporate innovation have a positive impact on firms' successful exits.

In the second chapter, co-authored with Thomas Chemmanur and Karthik Krishnan, we hypothesize that VC-backing garners greater "investor attention" (Merton (1987)) for IPOs, allowing IPO underwriters to perform two information-related roles more efficiently during the book-building and road-show process: information dissemination, where the lead underwriter disseminates noisy information about various aspects of the IPO firm to institutional investors; and information extraction, where the lead underwriter extracts information useful in pricing the IPO firm equity from institutional investors. Using pre-IPO media coverage as a proxy, we show empirically that VC-backed firm IPOs indeed obtain greater investor attention, causally yielding them more favorable IPO characteristics such as higher IPO and secondary market valuations.

In the third chapter, co-authored with Thomas Chemmanur, Lei Kong, and Karthik Krishnan, using panel data on top management characteristics and a management quality factor constructed using common factor analysis on individual management quality proxies, we analyze the relation between the human capital or "quality" of firm management and its innovation inputs and outputs. We control for the endogenous matching between firm and management quality using a plausibly exogenous shock to the supply of new managers as an instrument, thereby finding a causal relationship between management quality and innovation activities. We show that higher management quality firms achieve greater innovation output by hiring more and higher quality inventors.

1 Do Venture Capital-Driven Top Management Changes Enhance Corporate Innovation in Private Firms?

1.1 Introduction

The role of venture capital (VC) in creating value for the entrepreneurial firms has been widely debated in the literature. At least since the early work of Gorman and Sahlman (1989), a number of studies have suggested that venture capitalists take an active role in the portfolio companies that they finance beyond providing capital (see, e.g., Lerner (1995) and Hellmann and Puri (2002)). One channel through which VCs may add value to their portfolio companies is by improving their management team, either by adding new managers in areas where the firm is lacking in managerial expertise or by removing managers who underperform. Further, VC investments typically focus on high technology and high growth sectors of the economy, such as information technology, life sciences, and energy technology (Da Rin, Hellmann, and Puri (2013)), where innovation is a critical driver of their long-term growth and competitive advantage. This means that one measure by which one can judge the effectiveness of venture capitalists in recruiting new managers or removing underperforming managers is by studying the effect of such venture-driven top management changes on the innovativeness of their portfolio companies. However, to the best of my knowledge, there is little analysis of the relation between top management changes and corporate innovation in venture-backed private firms. In this paper, I use a unique hand-collected dataset to fill this gap in the literature by providing new evidence on how top management changes affect corporate innovation in venture-backed private firms and on the possible mechanisms through which this occurs.

I explore several interesting research questions regarding the effect of top management changes on corporate innovation. First, do top management changes lead to more and higher quality innovation? Second, is the probability of top management changes in venture-backed firms higher in firms where VCs have greater power (e.g., greater board membership)? Further, is the relation between top management changes and corporate innovation stronger in such firms? Third, as top management changes may include adding new managers as well as removing existing managers, how does each of these actions affect corporate innovation? Fourth, what type of top management background (in terms of educational and employment experience) is important in spurring innovation? In particular, are managers with general managerial skills (having worked as a CEO in another company), or those with a prior technical background (having engaged in the research and development process themselves), or both, important in spurring innovation?[1] Fifth, what are the underlying mechanisms through which top management changes affect corporate innovation in venture-backed private firms? Finally, how do top management changes and enhanced innovativeness affect the probability of a successful exit (either through an IPO or an acquisition) of venture-backed private firms?

The empirical analysis of the relation between top management changes and corporate innovation in venture-backed private firms is hampered by two major challenges. First, the data (especially management team and board of directors data) on venture-backed private firms is very limited. Second, potential endogeneity may confound any empirical analysis on the relation between top management changes and corporate innovation. On the one

[1] Anecdotal evidence suggests that venture-backed entrepreneurial firms may add seasoned CEOs as well as top managers with a prior technical background to help firms succeed. For example, SpaceClaim Corporation, a provider of 3D Modeling Software based in Concord, Massachusetts, announced the addition of Michael McGuinness (a seasoned CEO and President with rich software industry experience) to its top management team right before it received the third round of VC financing. SpaceClaim commented that McGuinness brought to SpaceClaim "broad executive experience across several industries" and strategic vision in high technology, management, and business development. See more details at http://www.spaceclaim.com/fr/company/news/pressreleases/07-03-20/SpaceClaim_Announces_Addition_of_Michael_McGuinness_as_Chief_Operating_Officer.aspx. An example of a venture-backed firm that added a top manager with a prior technical background is Acceleron Pharma, Inc., a biopharmaceutical company based in Cambridge, Massachusetts. Acceleron announced the appointment of Matthew L. Sherman, M.D. (who was responsible for clinical research and clinical operations in another pharmaceutical company prior to joining Acceleron and published a number of research papers) as Senior Vice President and Chief Medical Officer when it received VC financing in 2006. The company claimed that the addition of Sherman brought to Acceleron "broad scientific and clinical research knowledge along with his experience and proven record of building clinical development organizations." See more details at http://investor.acceleronpharma.com/releasedetail.cfm?ReleaseID=785744.

hand, one may argue that the relationship between top management changes and corporate innovation may be largely driven by omitted variables such as the underlying quality (innovativeness) of the firm, i.e., both top management changes and corporate innovation may be positively related to firm quality, in which case OLS regression estimates linking top management changes and corporate innovation will be biased upwards. On the other hand, venture capitalists may be more likely to intervene in firms (i.e., induce management changes) when they are performing poorly in order to help them improve their performance, in which case OLS regression estimates will be biased downwards.

I overcome the first challenge by constructing a unique hand-collected dataset of top management team and board information of venture-backed private firms, using which I can identify the top managers as well as board of directors for each firm across different financing rounds. I begin with all the venture-backed deals covered in VentureXpert over the period of 2002-2010 and hand-collect top management team and board information for these venture-backed private firms in each financing round from their "Form D" filings on the SEC EDGAR website. Many venture-backed firms use exemptions under Regulation D, which allow them to sell equity to accredited investors (such as venture capitalists) without having to register with the SEC and become a public company. When relying on Regulation D, firms are required to file a Form D, which is a brief notice that contains important information about the firm and the offering, including the names and addresses of the firm's executive officers (such as CEO, president, Chief Technology Officer) and directors, the amount of investment made by investors, and the date of sale.

I overcome the second challenge related to endogeneity using an instrumental variable analysis. I instrument for top management changes using a plausibly exogenous shock to the supply of outside managers that are able to move across firms and are available for hire by venture-backed private firms. Specifically, the instrument that I use is the number of acquisitions made by established firms in the same industry and in the same state as the venture-backed private firm multiplied by an index measuring the enforceability of non-compete clauses in that state. This instrument is motivated by the following facts. First, incoming managers to startups often come from established firms, and these firms are dominant players in the acquisition market. In other words, there is a strong correlation between the movement of executives across firms and the number of acquisitions made by established firms in the industry. Second, the enforceability of non-compete clauses, which are commonly used in employment contracts for top management to prohibit them from joining or founding a rival company, affects the mobility of managers across firms. In each stage of my IV regressions, I include industry-by-year and state-by-year fixed effects to absorb any industry-wide technology shock and any local economic shock that may affect innovation. Therefore, my instrument is unlikely to affect innovation through channels other than through its effect on the the ease of recruiting top management, thus satisfying the exclusion restriction.

My empirical results can be summarized as follows. First, I find that top management changes are associated with significantly more and higher quality corporate innovation subsequent to top management changes (as measured by patent counts and patent citations) in venture-backed private firms. For example, two-year patent counts and two-year patent citations increase by 14% and 11.7%, respectively, following top management changes. Second, I show that the probability of management changes is increasing with the power of venture capitalists in the firm (as measured by the number of outside board members), suggesting that management changes in my venture-backed sample are primarily driven by venture capitalists.[2] Further, I find that the effect of management changes on corporate innovation is stronger for firms where venture capitalists have greater power, consistent with the conjecture that venture capitalists add value to their portfolio companies through inducing management changes. My instrumental variable analysis (making use of a plausibly exoge-

[2] I follow the existing literature (see, e.g., Ewens and Marx (2014)) in making use of the number of outside board members as a measure for the power of VCs in the firm. Typically, outside board members in venture-backed private firms are composed of investors (e.g., VCs) and independent observers (see Kaplan and Strömberg (2003) and Ewens and Marx (2014) for details). The existing literature has documented that other outside board members are likely to vote along with VCs (especially when the venture-backed firm performs poorly), thus justifying the use of the number of outside board members as a proxy for the power of VCs in the firm.

nous shock to the supply of outside managers as described above) shows that the positive relationship that I documented earlier between management changes and corporate innovation is causal. Third, I find that adding new managers has a positive and significant effect on the quantity and quality of future innovation, while removing existing managers does not. Fourth, I find that adding seasoned CEOs has a positive and significant effect on innovation, while adding senior managers with a prior technical background does not.

I then investigate the possible underlying mechanisms through which top management changes may foster greater innovation activities. I hypothesize that the new management teams may select and allocate resources to higher quality innovation projects, manage innovative assets more efficiently, and provide a better environment for inventors (i.e., scientists and engineers) to succeed in the firm (for example, by creating a more failure-tolerant environment for inventors, in the sense of Manso (2011)). Thus, one way that top management changes may enhance corporate innovation is by the new management team being able to hire more inventors to work for the firm (for a given amount of resources available). My result is consistent with this conjecture: I find that top management changes are associated with a significantly greater net inflow (inflow minus outflow) of inventors in the two or three years following top management changes. Further, the positive relation between top management changes and the net inflow of inventors is stronger for firms where VCs have greater power.

Finally, I explore the relation between top management changes, corporate innovation, and successful exit outcomes (as measured by an IPO or an acquisition by another company) in venture-backed private firms. I find that both management changes and innovation output are significantly and positively related to the probability of successful exit outcomes. I also show that the effect of top management changes on the successful exit is at least partly mediated through enhanced innovation.

I conduct a number of robustness tests and find that the positive relation between top management changes and corporate innovation that I documented earlier is robust to these tests. First, I find that the positive relation between management changes and corporate innovation is robust to controlling for industry-by-state-by-year fixed effects. As my instrumental variable analysis makes use of variation at the industry-by-state-by-year level, this helps to alleviate the concern that that industry-by-state-by-year level omitted variables may drive both management changes and corporate innovation. Second, to alleviate the concern that corporate innovation may be driven by a general trend of technological development, I conduct a placebo test using innovation output generated prior to management changes as the dependent variable. I find that the relation between management changes and prior innovation is insignificant, suggesting that the positive relation between management changes and future innovation is unlikely to be due to a general trend of technological development. Third, I show that the positive relation that I documented earlier between top management changes and corporate innovation is robust to controlling for lead VC firm fixed effects. The results of this robustness test confirm that the positive relation between top management changes and innovation is not driven by any unobservable and time-invariant VC firm characteristics that may affect innovation (such as VC firms' project selection ability and preferences).

My paper is related to a number of studies and contributes to several strands in the literature. First, it improves our understanding on how venture capitalists add value to the entrepreneurial firms that they invest in through active intervention in recruiting top management. Several existing studies show that VCs play a role in recruiting managers (especially CEOs) and replacing founders. For example, Hellmann and Puri (2002) use a sample of 170 Silicon Valley startups and show that venture capitalists professionalize nascent firms by instituting human resource policies and bringing in professional CEOs to replace founders. They, however, do not study the effect of such management changes on any subsequent outcomes (including innovation). Wasserman (2003) shows that raising financing from outside investors (mainly VCs) leads to higher chances of founder-CEO being replaced by an outside CEO, using a sample of 202 Internet startups. Amornsiripanitch, Gompers, and Xuan (2016) show that successful VCs who have a good track record of past investment and a large network are likely to hire outside managers and outside board members. Ewens and Marx (2014) find that venture capitalists are more likely to replace senior managers in struggling startups to "correct the ship" and establish a causal relationship between management replacements and better exit outcomes. In summary, none of the above papers study the relationship between top management changes and product market innovation in venture-backed private firms, which is the focus of this paper.

Second, my paper adds to the literature on how venture-backing improves innovation or efficiency, by establishing the link between a specific action by venture capitalists (i.e., top management changes) and corporate innovation. Several papers study how VC-backing affects innovation in venture-backed firms, relative to non-venture-backed firms, while other studies attempt to identify the relationship between VC characteristics (such as experience, industry expertise, syndication, staged capital infusion, and failure tolerance) and innovation in venture-backed firms. Recent studies include Chemmanur, Loutskina, and Tian (2014), Tian (2011), and Tian and Wang (2014), Bernstein, Giroud, and Townsend (2015), etc. Another literature is the one studying whether VC-backing improves efficiency in private firms and the mechanisms through which they do so (see, e.g., Chemmanur, Krishnan, and Nandy (2011)).[3]

Third, this study sheds significant light on the top management changes/turnover literature. Existing studies have shown that management changes are important corporate events. In particular, there is empirical evidence documenting improvements in accounting and stock performances following CEO turnover mainly for large public companies (Huson, Malatesta, and Parrino (2004); Denis and Denis (1995); Cornelli, Kominek, and Lungquivst (2013)). Bereskin and Hsu (2013) study the effect of CEO turnover on corporate innovation in large public companies. However, with a few exceptions (Gao, Harford, and Li (2015) and Cornelli and Karakaş (2015)), the literature above focuses on the publicly traded firms and

[3]See Da Rin, Hellmann, and Puri (2013), who provide an excellent survey of the broader venture capital literature.

provides few insights into management changes in private firms due to data limitations.[4] My paper adds to the literature by examining for the first time, the effect of top management changes on corporate innovation in venture-backed private firms.

Finally, this study proposes a channel through which top management changes may affect corporate innovation, suggesting that the new management team may enhance innovation by attracting a greater number of inventors. Thus my study contributes to a small but growing literature on labor mobility and innovator flows (e.g., Marx, Strumsky, and Fleming (2009) and Chemmanur, Kong, Krishnan, and Yu (2016)).

The rest of the paper is organized as follows. Section 1.2 discusses the underlying theory and develops testable hypotheses. Section 1.3 outlines the data and the sample selection procedure. Section 1.4 provides a discussion of my main empirical tests and results. Section 1.5 presents a discussion of my robustness test results. Section 1.6 concludes.

1.2 Theory and Hypothesis Development

In this section, I briefly review the underlying theory and develop testable hypotheses for my empirical tests. Existing literature offers several explanations for why management changes can create firm value. One view is that top management changes are part of an error correction process. The new management teams may reverse the bad decisions of past management teams and reallocate resources to more promising projects (e.g., Boot (1992) and Weisbach (1995)).[5] Another view is that new managers may bring additional resources to the firm (such as additional human capital) and may establish complementarities between these new resources and existing human capital, which can create value for the firm (e.g.,

[4] Gao, Harford, and Li (2015) find that public firms have higher CEO turnover rates and exhibit greater CEO turnover-performance sensitivities than large private firms, using a sample of US public firms and large private firms. Cornelli and Karakaş (2015) find that CEO turnover decreases and is less contingent on performance when a firm is taken private, using a sample of LBO firms in the UK.

[5] Boot (1992) theorizes that unskilled managers are reluctant to divest because a divesture is an admission of a mistake. Therefore, on average, there is too little divesture relative to the shareholders' optimum. Consistent with Boot's implications, Weisbach (1995) finds that the probability of divesting poorly performing projects increases after CEO turnover.

Oyer and Schaefer (2011), Pan (2015), and Huang (2014)).[6] Based on both theories, if the new management team can correct bad decisions and reallocate resources to more innovative projects, or if they can bring additional human capital enabling them to select more innovative projects and manage these projects more ably, I would expect management changes to be associated with significantly more and higher quality corporate innovation output. This is the first hypothesis that I test here (**H1**).

Existing studies have suggested that VCs provide value-added services to the companies that they finance. They are known to take an active role in recruiting senior management, either by bringing in new (and professional) managers to expand the management team or by removing existing managers (see, e.g., Gorman and Sahlman (1989), Lerner (1995) and Hellmann and Puri (2002)). If management changes in venture-backed private firms are likely to be driven by venture capitalists, i.e., venture capitalist proactively add or remove managers in the firms they back to help them succeed rather than replacing managers who resign from the firm voluntarily (possibly due to getting attractive outside opportunities or losing interest in the current firm), then I would expect the probability of top management changes to increase with the power of venture capitalists in the firm. Further, if management changes are truly a source of value-addition, I would expect the effect of management changes on innovation to be stronger for firms where VCs have greater power. This is the second hypothesis that I test here (**H2**).

As top management changes may include adding new managers as well as removing existing mangers (or both), I then explore how each of these actions may affect corporate innovation. As suggested in existing studies (e.g., Boot (1992)), removing existing managers may result in correcting past errors in terms of investment and other decisions, such as

[6]Oyer and Schaefer (2011) suggest that management attributes (such as talents, skills, or experience) may complement certain production technologies and improve productivity of the firm. Pan (2015) uses a model of executive-firm matching and shows that complementarity between the firm and management attributes may lead to increased productivity of the firm. Huang (2014) investigates how the complementarity between managers' industry experience and the firm affects firm value. His empirical findings show that CEOs in conglomerates are more likely to refocus on divisions in which they have specialized and divest those in which they have less experience.

abandoning poorly performing projects. If so, I would expect removing existing managers to be positively related with the quantity and quality of innovation. Further, if top management changes are indeed a source of value-addition by VCs, I would expect the relation between removing existing managers and innovation to be stronger in firms where VCs have more power (**H3**). Existing studies (e.g., Oyer and Schaefer (2011)) also suggest that adding new managers may bring in new blood to the firm's existing human capital, in addition to correcting past errors. If so, I would expect adding new managers to be positively related to the quantity and quality of corporate innovation. Further, I expect such a relation to be stronger in firms where VCs have more power (**H4**). These two relations are not mutually exclusive and both may exist from *a priori* theoretical considerations.

Further, I delve deeper into the background of the new management teams and study how different background of the managers may play a role in affecting innovation. One possibility is that the new managers with general managerial skills (for example, who have worked as a CEO or president before) are better at allocating resources, managing assets, and attracting human capital and thus enhance innovation. If so, I would expect adding seasoned CEOs (or presidents) to the firm's top management team (not necessarily as a CEO or president) to have a positive effect on the quantity and quality of innovation (**H5**). Another possibility is that the new managers with a prior technical background (for example, who either hold a research degree in a field related to the firm's business or have engaged in the research and development process in another company) are better at selecting innovative projects to invest in and participating in the development process due to their technical skills and research experience. If so, I would expect adding such managers to have a positive effect on the quantity and quality of innovation (**H6**). Again, these two effects are not mutually exclusive to each other and both may exist.

I now turn to an analysis of the possible underlying mechanisms through which management changes may enhance corporate innovation in venture-backed firms. One possible mechanism is through the inventor mobility channel. New management teams may select and allocate resources to more innovative projects, manage innovative assets better, and provide a better environment for inventors to succeed (for example, by creating a more failure-tolerant environment for inventors, in the sense of Manso (2011)). This, in turn, may enable the firm to attract more inventors. Therefore, I would expect management changes to be associated with a greater net inflow of inventors. Further, if VCs have greater power in the firm, they may be more effective in using top management changes to create value for the firm through the inventor mobility channel. I would therefore expect the effect of management changes on the net inflow of inventors to be stronger in firms where VCs have greater power (**H7**).

Finally, I investigate the effect of venture capital-driven top management changes as well as enhanced innovation output on the probability of successful exit (either through an IPO or an acquisition) for venture-backed firms. First, if one of the ways in which venture capitalists add value to a firm that they invest in is by inducing top management changes when appropriate (either by adding or removing managers), then I would expect such top management changes to be positively associated with the probability of successful exit (**H8**). Second, since successful innovations are likely to be associated with positive net present value investment opportunities, I would expect firms with greater innovative success to be associated with a higher probability of a successful exit (**H9**).

1.3 Data and Sample Selection

1.3.1 Sample Selection

My sample is derived from multiple data sources. I begin with all the VC-backed deals (VC investments) with at least two financing rounds over the period of 2002-2010 covered in the VentureXpert database. I require that the first round information and the amount of investment made by VCs for all the rounds must be available. This leaves us with 19201 firm-financing round observations and 1777 distinct venture-backed firms. Then I randomly select 50% of these firms for hand collection of the information of their management team and board of directors.[7]

I hand-collect the management team and board member information for each selected firm from the "Form D" filings on the SEC website. Under the Securities Act of 1933, any offer to sell securities must either be registered with the SEC (which will make the company selling securities a public company) or meet an exemption. Regulation D (or Reg D) contains three rules providing exemptions from the registration requirements, i.e., the Reg D private placement is an equity-financing alternative to a public offering. Many venture-backed private firms use exemptions under Reg D to sell equity to the venture capitalists. Firms relying on a Reg D exemption are required to file a "Form D," which is a brief notice that includes the names and addresses of the company's top managers (such as CEO, president, Chief Technology Officer, and VP Finance), board of directors, size of the offering, and date of the sale.[8,9] Therefore, for each firm-financing round observation in the selected deals from the VentureXpert database as described above, I search the firms for their Form D filings on the SEC EDGAR website based on the name of the company, the filing date, and the amount of investment by VCs and hand-collect the names of each member on the management team as well as board of directors for these venture-backed firms.

I hand-collect firm-year patent and citation information from the USPTO website based on the names and addresses of the venture-backed entrepreneurial firms in my sample. I collect the inventor information associated with each patent from the U.S. Patent Inventor Database (1975-2010) (see Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014)). Information on the successful exit outcomes of these venture-backed entrepreneurial firms (as measured by an IPO or an acquisition by another company) comes from the SDC Global

[7]In the current stage, I randomly select 50% of the deals for hand collection. I compared the distribution of the selected deals with the whole sample and confirm that the selected deals are representative of the whole sample.

[8]See a detailed description about Form D at http://www.sec.gov/answers/formd.htm.

[9]Although firms are not required to disclose each manager's specific title in Form D, they have to disclose the names and titles of the managers who signed the document. From the names and titles of these signers, I am able to identify the titles of the managers that may be included in Form D.

New Issues database and the SDC Mergers & Acquisitions database, respectively.

The final merged sample results in 434 firms and 977 firm-financing round observations.[10] Most of my sample firms stay private and active under VC investment over 2002-2010, while about 5% of the these firms exited through an IPO and 21% of them exited through an acquisition within ten years after receiving the first round of VC financing.[11] A typical venture-backed firm in my sample receives $5.5 million investment from VCs per round. The median number of investors in a syndicate is 2. Firms headquartered in Massachusetts and California account for 15% and 41% of the sample firms, respectively. These statistics of my sample are comparable to those documented in the existing literature (e.g., Tian (2011) and Ewens and Marx (2014)).

1.3.2 Measures of Top Management Changes

The main explanatory variable, *Mgmt Change*, is an indicator variable equal to one for a firm-financing round if the composition of the firm's top management team in the current round is different from that in the previous round and zero otherwise. Specifically, the indicator is turned on if either new managers were added to the top management team or existing managers from the previous financing round were removed from the top management team in the current round. As management changes may include adding new managers to expand team, removing existing managers from the team, or both, I therefore create three separate indicators for each of the above three cases. *Add Only* is a dummy variable equal to one if new managers were added to the management team for a firm-round but no existing managers were removed, and zero otherwise; *Remove Only* is a dummy variable equal to one if existing managers were removed from the management team for a firm-round but no new managers were added, and zero otherwise; *Both* is a dummy variable equal to one if new managers were added to and existing managers were removed from a firm's management team as well

[10] If a firm receives more than one round of VC financing within one year, I aggregate these observations into one firm-round year observation.

[11] In total, 25% of the sample firms were eventually acquired by another company.

for a firm-round observation, and zero otherwise. I also use two sets of continuous variables, namely, the natural log of one plus the number (or fraction) of new managers added and the natural log of one plus the number (or fraction) of existing managers, as alternative measures for adding new managers and removing existing managers.

1.3.3 Measures of Corporate Innovation

Following the existing literature (e.g., Hall, Jaffe, and Trajtenberg (2001), Chemmanur, Loutskina, and Tian (2014), and Seru (2014)), I use patent-based metrics to capture firm innovativeness. I hand-collect the patent information associated with each firm in my venture-backed sample based on the name and address of the firm from the USPTO website.[12]

Patent data is subject to two types of truncation bias. First, patents are recorded on the USPTO website only after they are granted and the lag between patent applications and patent grants is significant (about two years on average). Therefore, we observe a smaller number of patent applications that are eventually granted towards the end of my sample period. Many patent applications filed during these years were still under review and had not yet been granted. I mitigate this bias by restricting my analyses to patents that are filed up to 2010. The second type of truncation problem is stemming from citation counts (i.e., the total number of citations received till now). Patents tend to receive citations over a long period of time, so the citation counts of more recent patents are significantly downward biased. Following Seru (2014), this bias is accounted for by scaling citations of a given patent by the mean number of citations received by all patents in that year in the same 3-digit technology class as the patent. Note that the above methodology gives us class-adjusted measures of patents and citations, which adjust for trends in innovative activity in particular industries.

Specifically, I use the following variables to measure the quantity and quality of innovation output, respectively: $Patents^{(N)} = Ln(1 + \sum_{\tau=1}^{N} Patents_{i,t+\tau})$, and $Cites^{(N)} =$

[12] I collected the patent data from the USPTO website in March, 2015. Therefore, my patent sample includes patents that were granted up to March, 2015.

$Ln(1 + \sum_{\tau=1}^{N} Cites_{i,t+\tau})$, where $N = 2$ or 3.[13] These proxies represent the natural log of one plus patent counts and citation counts over the following two or three years, and the log-linearization is used to mitigate skewness following Lerner (1995). $Patents_{i,t}$ is firm i's patent counts in year t, defined as the total number of patent applications filed by firm i in year t that were finally granted. $Cites_{i,t}$ is firm i's patent citations in year t, defined as the number of adjusted number of citations received by all patents filed by firm i in year t. Table 1 reports the summary statistics for my innovation measures. For example, $Patents^{(2)}$ has a mean value of 0.50 and a median value of zero; $Cites^{(2)}$ has a mean value of 0.40 and a median value of zero.

1.3.4 Measures of Inventor Mobility

To identify the inventor mobility, I collect inventor information of each patent from the U.S Patent Inventor Database (1975-2010) (see Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014)). The U.S. Patent Inventor Database includes inventor names, inventor addresses, assignee names, application date, and grant date for each patent. More importantly, it identifies unique inventors over time so that we could possibly track the moves of each inventor. Following Marx, Strumsky, and Fleming (2009), I identify mobile inventors as changing employers if he has ever filed two successive patent applications that are assigned to different firms (or organizations). As I need at least two patents to detect a move, inventors that have filed a single patent throughout their career are necessarily excluded from my analysis.

I assume the inventor's move to occur in the year when he filed his first patent in a given firm. For a given firm, an inventor's move-in year is the year when he filed his first patent in this firm; the inventor's move-out year is the year when he filed his first patent in the subsequent firm. For the inventor's very last employer, I assume that the inventor stayed

[13] In untabulated analyses, I conduct regressions using these dependent variables where N=4 or 5. The results are qualitatively similar but weaker due to decreased sample size.

with that firm and did not move out.[14] For example, in the inventor database, an inventor named Christopher L. Holderness has filed two patent applications till 2010. He filed patent application with Corning Inc. in 1999 and then with Dell Inc. in 2003. In accordance with my assumption, for Corning, Mr. Holderness's move-in year is 1999 and move-out year is 2003; and for Dell, Mr. Holderness's move-in year is 2003, and he has stayed with Dell since 2003. Once I identify each mobile inventor's move-in and move-out year, I aggregate the number of mobile inventors that move in and move out at the firm-year level to obtain the total inflow and outflow of mobile inventors for a given firm in a year. I define the difference between the natural logarithm of one plus the inflow and the natural logarithm of one plus the outflow as the net inflow of mobile inventors. For firms without any mobile inventors, I assign zero values to the inflow, outflow, and net inflow of mobile inventors. I use the following variables to measure the cumulative inflow, outflow, and net inflow of mobile inventors in the next N years following management changes, respectively: $\mathit{Inflow}^{(N)} = \mathit{Ln}(1 + \sum_{\tau=1}^{N} \mathit{Inflow}_{i,t+\tau})$, $\mathit{Outflow}^{(N)} = \mathit{Ln}(1 + \sum_{\tau=1}^{N} \mathit{Outflow}_{i,t+\tau})$, and $\mathit{Net\ Inflow}^{(N)} = \mathit{Inflow}^{(N)} - \mathit{Outflow}^{(N)}$, where N=2 or 3.

1.3.5 Other Variables

I control for the following characteristics and fixed effects that may affect firms' innovation output following the literature (see, for example, Chemmanur, Loutskina, and Tian (2014), Tian (2011), Chemmanur, Krishnan, Kong, and Yu (2016), and Tian and Wang (2014)). In the baseline regressions, my control variables include the following: *Ln(VC Investment)*, which is defined as the natural log of the VC investment amount for a firm-financing round; *Ln(Syndicate Size)*, which is defined as the natural log of one plus the number of investing VCs; and *Ln(Mgmt Team Size)*, which is defined as the natural log of one plus the number of managers in a firm's top management team. Table 1 provides summary statistics for the

[14] As a robustness check, I redefine the dates that the inventor moved out of his last employer as one or two years after he filed his last patent in that firm. My results remain qualitatively similar with this alternative definition.

control variables described above. For example, *Ln(VC Investment)* has a mean value of 8.48 and a median value of 8.61. A typical firm in my sample has a top management team composed of two senior managers and receives VC funding from three syndicating venture capitalists. In all regressions, I also include industry fixed effects (defined at the 2-digit SIC code level), year of financing round fixed effects, and development stage fixed effects, unless otherwise specified.

1.4 Empirical Results

1.4.1 The Effect of Top Management Changes on Corporate Innovation

I expect top management changes to be associated with significantly more and higher quality corporate innovation, as measured by patent counts and the total number of citations, respectively. In this section, I empirically test this hypothesis (**H1**) by estimating the following model:

$$Innovation^{(N)} = \alpha + \beta Mgmt\ Change_{i,t} + \gamma Z_{i,t} + Industry + Year + Stage + \epsilon_{i,t}, \quad (1.1)$$

where i indexes firm and t indexes time and N equals two or three. $Innovation^{(N)}$ are the two-year or three-year patent counts and patent citations described earlier. Since the innovation process takes time, I examine the cumulative effect of a firm's management changes on its innovation within two or three years following management changes.[15] The main explanatory variable, *Mgmt Change*, is measured for firm i over year t, which is the year of the current financing round. Z is a vector of control variables that may affect a firm's innovation output, which includes *Ln(VC Investment)*, *Ln(Syndicate Size)*, and *Ln(Mgmt Team Size)*, as described in Section 1.3.5. Industry fixed effects (defined at 2-digit SIC code level), year fixed effects, and development stage fixed effects are also included. In all regressions

[15] As mentioned in Section 1.3.3, using dependent variables defined over longer horizons (i.e., within the next four or five years) gives qualitatively similar but weaker results due to decreased sample size.

throughout the paper, standard error are clustered at the industry level unless otherwise specified.

Table 2 reports the OLS estimation results for regression (1.1). Columns (1) and (2) report results for the regressions using the cumulative two-year patent counts and patent citations as dependent variables, respectively; while Columns (3) and (4) report results for the regressions using the cumulative three-year patent counts and patent citations, respectively. In almost all the specifications, the coefficients on *Mgmt Change* are positive and significant at least at the 5% level. The coefficient in Column (4) is still positive but becomes insignificant due to increased standard errors. The economic magnitude of the effect of management changes on innovation is significant as well: for example, Column (1) suggests that two-year patent counts increase by 14% following management changes, and Column (2) suggests that two-year patent citations increase by 11.4% following management changes. Collectively, these results suggest that management changes are associated with significantly more and higher quality future innovation, which is consistent with **H1**.

1.4.2 The Effect of Top Management Changes on Corporate Innovation for Firms with Different VC Power

The results in the above section suggest a positive link between management changes and corporate innovation. In this section, I first show that top management changes in my venture-backed sample are likely to be driven by venture capitalists. Then I explore whether the positive relation between venture-driven management changes and corporate innovation is stronger for firms where VCs have greater power.

As argued earlier, if venture capitalists proactively add or remove managers in venture-backed firms to help them succeed rather than replacing managers who resign from the firm voluntarily due to having attractive outside opportunities or losing interest in the firm, then I would expect that the probability of management changes increases with the power of VCs. I use the number of outside board members (i.e., board members that are not on the management team) to assess the power of VCs in venture-backed private firms. The board of a firm is known to be responsible for hiring, monitoring, and firing top management team. The board of directors in venture-backed entrepreneurial firms are usually composed of insiders (executive officers or founders), investors (e.g., VCs), and independent directors (who are mutually agreed upon both by investors and insiders, see Kaplan and Strömberg (2003) and Ewens and Marx (2014) for more details). Existing studies document that other outside board members are likely to vote along with VCs (especially when the firm performs poorly), thus justifying the use of outside board members as a proxy for the power of VC in the firm.[16]

To test whether management changes are likely to be driven by VCs, I estimate the following probit model using the *Mgmt Change* as the dependent variable:

$$\mathit{Prob(Mgmt\ Change)}_{i,t} = \alpha + \theta\, \mathit{VC\ Power}_{i,t} + \gamma Z_{i,t} + Industry + Year + Stage + \epsilon_{i,t}, \quad (1.2)$$

where *VC Power* is measured by the natural log of one plus the number of outside board members.[17] I use the fraction of outside board members as an alternative measure. As the existing literature also documents that firm age may be an important determinant of the probability of management changes, I include *Ln(Firm Age)* as a control variable in addition to the set of controls used earlier.

Table 3 reports the results for the above probit model. Columns (1) uses natural log of one plus the outside board members as a proxy for the power of VCs in the venture-backed firm. The coefficient on *Ln(Outside Board Members)* is positive and significant at the 1% level, with the predicted sign. The economic magnitude of the effect of VC power on changes is very significant. For example, the estimate in Column (1) implies that a one

[16]Existing studies show that outside board members are likely to play a role in changing management in venture-backed private firms (see, e.g., Kaplan and Strömberg (2003) and Ewens and Marx (2014)). Studies on the boards of public firms such as Weisbach (1988) and Knyazeva, Knyazeva, and Masulis (2013) show that the outside board size or board independence are connected with shareholder power and have a direct effect on CEO turnover.

[17]I add one to the the number of outside board members before taking logs to avoid losing observations.

standard deviation increase in the log of the number of outside board members (0.49) is associated with a 9.1% increase in the probability of a management change.[18] Column (2) uses the fraction of outside board members as the main explanatory variable. As expected, the coefficient on *Fraction of Outside Board Members* is significantly positive. A one inter-quartile increase in the fraction of outside board members (0.3) is associated with 12.7% increase in the probability of a management change. Overall, the results in Table 3 provide strong evidence that management changes in my sample of venture-backed private firms are likely to be driven by venture capitalists.

Next, I use an interaction test to study whether the effect of management changes on corporate innovation is stronger for firms where VCs have greater power. I therefore interact *Mgmt Change* with an indicator for greater VC power (*High Power*) and test the following model:

$$\begin{aligned} Innovation^{(N)} &= \alpha + \beta Mgmt\ Change_{i,t} + \delta High\ Power_{i,t} + \theta Mgmt\ Change_{i,t} \times High\ Power_{i,t} \\ &\quad + \gamma Z_{i,t} + Industry + Year + Stage + \epsilon_{i,t}, \end{aligned} \tag{1.3}$$

where *High Power* is defined as a dummy variable equal to one if the number of outside board members is above the sample median and zero otherwise. Table 4 reports the results for these interaction tests. Consistent with my earlier conjectures, I find that the coefficient on the interaction between *Mgmt Change* and *High Power* is positive and significant at least at the 5% level for all the specifications. Once the interaction terms are included in the regressions, the effect of *Mgmt Change* becomes insignificant. These findings suggest that venture-driven management changes are more effective in enhancing innovation in firms where VCs have greater power, consistent with the notion that VCs add value to their portfolio companies through actively improving firm management. In sum, the results in this section lend support

[18] The predicted probability of a management change at the mean of control variables is 20.9%. Fixing means while increasing the outside board size by one standard deviation (0.49) results in a predicted probability of 30.1%.

for **H2**.

1.4.3 The Effect of Top Management Changes on Corporate Innovation: Instrumental Variable Analysis

In my baseline (OLS regression) analysis, I find a positive association between top management changes and enhanced innovation activities subsequently in venture-backed private firms. However, potential endogeneity can confound empirical findings from the baseline analysis linking management changes and corporate innovation. On the one hand, one may argue that the positive relationship between management changes and corporate innovation may be driven by omitted variables such as firm quality or innovativeness, as venture capitalist may select more innovative firms to invest in. In this case, the OLS estimates will be biased upwards. On the other hand, venture capitalists may be more likely to intervene the firms when they are off the track to help them "correct the ship." In this case, the OLS estimates will be biased downwards. In order to address the above potential endogeneity concerns, I conduct an instrumental variable (IV) analysis using a plausibly exogenous shock to the supply of outside managers available for hire (who might serve as suitable replacements). Specifically, my instrument is constructed as the number of acquisitions made by public companies in the same industry and in the same state as the venture-backed private firm multiplied by an index measuring the enforceability of the non-compete clauses in that state.

The instrument in my IV analysis is motivated by the following facts. First, incoming managers to startups often come from established firms, and these firms are dominant players in the acquisition market. In other words, there is a strong correlation between the movement of managers across firms and the number of acquisitions in the industry that the firm belongs to. Inspired by Ewens and Marx (2014), I count the number of acquisitions made by established firms in the same industry and in the same state as the venture-backed entrepreneurial firms two years prior as a proxy for the local supply of outside managers for the venture-backed firms.[19] The two-year lag stems from the popular retention contracts employed by the acquirers for target firms. These contracts often compensate the managers of target firms for lost compensation for two to four years and provide strong incentives for these managers to stay with the target firms for another few years. The expiration of these contracts generates a source of variation to the potential supply of managers. Second, the enforceability of non-compete clauses, which are commonly used in employment contracts for top management and prohibit them from joining or founding a rival company within one to two years of leaving, affects the mobility of managers across the firms.[20] Bishara, Martin, and Thomas (2015) analyze an extensive sample of CEO employment contracts and show that 80% of these contracts contain non-compete clauses, often with a broad geographic scope. A growing body of work (e.g., Garmaise (2009) and Marx, Strumsky, and Fleming (2009)) shows that higher enforceability of these non-compete clauses reduces employees' mobility (including that of managers). The enforceability of such non-compete clauses exhibits both cross-state and time series variation, which leads to variation in the mobility of managers that is unlikely to be directly related to innovation. Based on the above facts, I construct an instrumental variable for *Mgmt Change*, making use of the the strong correlation between industry acquisitions and the movement of top managers as well as the exogenous variation in the mobility of managers.

Specifically, the instrumental variable for *Mgmt Change* in a firm in industry j headquartered in state s in year t, is computed as follows:

$$Instrument_{j,t} = Acquisitions_{j,s,t-2} \times Enforceability\ Index_{s,t}, \tag{1.4}$$

where j, s, and t index industry, state, and year, respectively. $Acquisitions_{j,s,t-2}$ is the number of acquisitions made by established (public) companies in industry j in state s in

[19] Ewens and Marx (2014) find a strong reduced-form correlation between executive replacement and the number of acquisitions in the same industry two years prior.

[20] Since these non-compete clauses become operational only when top managers leave their prior firms, the enforceability of these non-compete clauses can be thought as a measure of the friction facing top managers when they attempt to join the venture-backed private firm.

year $t-2$. The information on mergers and acquisitions required to construct this variable is collected from the SDC Mergers & Acquisitions Database. Again, the two-year lag allows for the expiration of retention contracts that work as "golden handcuffs" for managers and thus $Acquisitions_{j,s,t-2}$ proxies for the potential supply of managers from state s in industry j in year t.

$Enforceability\ Index_{s,t}$ is the index measuring the enforceability of non-compete agreements across different US states based on Garmaise (2009). Garmaise (2009) develops an index to measure the enforceability of non-compete clauses by considering 12 questions analyzed by Malsberger (2004), which is the central resource describing noncompetition law in 50 US states and the DC, and assigning 1 point to each jurisdiction for each question if the jurisdiction's enforcement of that dimension of noncompetition law exceeds a certain threshold. Possible totals therefore range from 0 to 12.[21] The *Enforceability Index* used here is constructed as the difference between 12 and the value of Garmaise's (2009) index scaled by 12 and thus it potentially ranges from 0 to 1. Higher (lower) values of *Enforceability Index* indicates weaker (greater) enforceability of the non-compete clauses and thus greater (weaker) mobility of managers. The instrument therefore proxies for the supply of managers that are able to move across firms and available for hire by a venture-backed private firm in state s in industry j in year t. I expect my instrument to be positively and significantly related to the probability of top management changes (and empirically show this in my first-stage regression as in below).

To instrument for top managements change of firm i in industry j in year t, I therefore

[21] Higher values of Garmaise's (2009) index indicate higher enforceability of the non-compete agreements in this state and thus less mobility of the managers from this state. For example, Garmaise's index (2009) is equal to 0 for California and is equal to 9 for Florida after 1997.

run the first-stage probit regression of my IV analysis as follows:[22,23]

$$Prob(Mgmt\ Change)_{i,j,t} = \alpha + \beta Instrument_{j,t} + \gamma Z_{i,t} + Industry \times\ Year + State \times\ Year \\ + Stage + \epsilon_{i,t}. \tag{1.5}$$

In each stage of my IV regressions, I include industry-by-year fixed effects and state-by-year fixed effects. These fixed effects help to absorb any industry-wide technology shock (e.g. innovation wave) and any local economic shock that may affect innovation. Therefore, the instrument is unlikely to affect innovation through channels other than through affecting the supply of managers and inducing top management changes, thus satisfying the exclusion restriction.

Table 5 report the first and second-stage results of my IV analysis. Column (1) reports the first-stage probit result. I find that the coefficient on my instrument is positive and significant at the 1% level, even after controlling for industry-wide shock and local economic shock. Pseudo R-squared is as large as 36.7%. The first stage F-statistic (Cragg-Donald Wald F statistic) for the weak instruments tests is 72.29 and is above the critical value as suggested in Stock and Yogo (2005). These results indicate that the relevance condition is likely to be satisfied.

Columns (2)-(5) in Panels A of Table 5 report the second-stage results of my IV analysis. I find that management changes continue to have a significantly positive effect on the quantity and quality of subsequent innovation, even after accounting for the potential endogeneity concerns described earlier. Further, the coefficient estimates on *Mgmt Change* in my IV

[22]Since the endogenous variable *Mgmt Change* is binary, I use a probit model in the first stage, following Wooldrige (2010). I then compute the predicted probability ($\widehat{Mgmt\ Change}$) from the probit estimation in the first stage and use $\widehat{Mgmt\ Change}$ as the instrumental variable for *Mgmt Change* to estimate the effect of top management changes on corporate innovation. I obtain qualitatively similar results using linear models in each stage.

[23]As documented in Section 1.4.2, the power of VCs and firm age may be significant determinants of the probability of top management changes for a venture-backed private firms. I therefore include *Ln(Outside Board Members)* and *Ln(Firm Age)* as additional control variables in addition to those used in the baseline analysis, as described in Section 1.3.5.

regression results become larger compared with the OLS regression estimates, suggesting that the OLS regression estimates are downward biased. This is like due to the fact that venture capitalists are more likely to intervene in firms that do not perform well and therefore management changes are more likely to occur in such firms.

In Panel B of Table 5, I report the IV(2SLS) results for the regressions that use the interaction term between management changes and a dummy variable for greater investor power as the main explanatory variable.[24] I find that the interaction terms load significantly and positively in all the specifications. This is consistent with my earlier findings in Section 1.4.2 and lends support for **H2** that the effect of management changes on corporate innovation is more pronounced in firms where VCs have greater power.

1.4.4 The Effects of Adding New Managers and Removing Existing Managers on Corporate Innovation

As top management changes may include adding new managers as well as removing existing managers (or both), I examine in this section how each of these actions may affect innovation in venture-backed private firms. To do this, I create three separate dummy variables to indicate that only new managers were added (*Add Only*), that only existing managers were removed (*Remove Only*), and that both happened (*Both*), and use them as the main explanatory variables for innovation. I also use two sets of continuous variables, namely, the fraction and the number of managers added and removed, as alternative measures for adding and removing managers.

Panel A of Table 6 report the estimation results using *Add Only*, *Remove Only*, and *Both* as the main explanatory variables. Columns (1)-(4) show that, the coefficients on *Add Only* are positive and significant at the 5% level for almost all the specifications, while the

[24]Following Wooldrige (2010), I run the first-stage probit regression as shown in regression (3.8) and compute the predicted probability of a top management change ($\widehat{Mgmt\ Change}$). Then I use $\widehat{Mgmt\ Change}$ and $\widehat{Mgmt\ Change} \times High\ Power$ as instrumental variables for $Mgmt\ Change$ and $Mgmt\ Change \times High\ Power$ and conduct an IV (2SLS) analysis. The first-stage F-statistic (Cragg-Donald Wald F statistic) for the weak instrument test is 24.26, which is significantly larger than the critical value suggested in Stock and Yogo (2005).

coefficients on *Remove Only* are all insignificant. The coefficients on *Both* are positive and significant at the 10% level for the quantity of innovation but insignificant for the quality of innovation. The differences between coefficients on *Add Only* and those on *Remove Only* or *Both* are statistically significant at the 10% level for the two-year patent counts and patent citations regressions. These results lend support for **H4** but not for **H3**, suggesting that adding new managers to the top management team is the major drive that spurs innovation.

Panel B of Table 6 reports regression results using alternative measures for adding new managers and removing existing managers. Columns (1) and (2) report the effect of the fraction of new managers added as well as the fraction of existing managers removed on two-year patent counts and citations. Columns (3)-(4) report regression results using the log of the number of new managers added and that of existing managers removed as the main explanatory variables.[25] Consistent with the results reported in Panel A, I find that the coefficients on measures for adding managers are significantly positive for all the specifications, while the coefficients on measures for removing managers are much smaller and insignificant. The differences between coefficients on measures for adding new managers and those on measures for removing existing managers are statistically significant for most specifications. The economic magnitude of the effect of adding new managers on corporate innovation is significant as well. For example, a one standard deviation increase in the fraction of managers added (0.214) is associated with 6.6% increase in two-year patents and 5.4% increase in two-year patent citations following management changes.

I then turn to explore the effect of adding new managers as well as removing existing managers on innovation for firms with different VC power. To do this, I interact the three indicator variables for adding new managers, removing existing managers, and both with the dummy variable for greater VC power. I report the results for these interaction tests in Table 7. I find that the interaction term *Add Only* $\times$ *High Power* loads positively and

[25]Here I use the cumulative two-year patent counts and citations as the only set of dependent variables in order to save space. The regressions using the cumulative three-year patent counts and patent citations yield qualitatively similar results. These results are available from the author upon request.

significantly for Columns (1)-(3), which is consistent with the conjecture that bringing in new managers is a source of value addition by VCs and venture-driven management changes are more effective in enhancing corporate innovation if VCs have more power in the firm. The coefficients on the other two interaction terms are almost all insignificant, consistent with my earlier results reported in Table 6 that adding new blood to the management team plays a major role in enhancing innovation. Collectively, my results in this section provide support for my hypothesis **H4**.

1.4.5 The Background of New Managers and Corporate Innovation

I show in the previous section that adding new managers is the major drive that enhances corporate innovation. In this section, I dig deeper into the profile of each new manager added to the management team and explore how different background of these new managers (in terms of educational and employment experience) may play a role in enhancing corporate innovation. To do this, I search for and read the bios of each new manager in my sample on their personal website, their company's website, LinkedIn, or Bloomberg, etc., and collect information on their educational background and employment history. I then classify all the new managers that were added to the management team into two broad categories: seasoned CEOs or presidents (who have prior experience working as a CEO or president in another company) and managers with a prior technical background (who hold a doctoral degree in a field related to the firm's business, or who were previously engaged in research and development process in another company working as a Chief Technology Officer (CTO) or Chief Innovation Officer (CIO), or who were previously granted patents in a field related to the firm's business). If the new management teams are better at managing and attracting human capital (scientists and engineers) and thus foster innovation activities, I would expect that adding seasoned CEOs to have a positive and significant effect on corporate innovation. If the new management teams are better at generating innovation themselves, I would expect adding people with a prior technical background to have a positive and significant effect on corporate innovation. These two effects are not mutually exclusive and may coexist. To test these implications of the background of new managers on innovation, I estimate the following model:

$$
\begin{aligned}
Innovation^{(N)} = {} & \alpha + \beta_1 Ln(Seasoned\ CEOs\ Added)_{i,t} + \beta_2 Ln(Tech\ Mgrs\ Added)_{i,t} \\
& + \delta Add(Dummy)_{i,t} + \gamma Z_{i,t} + Industry + Year + Stage + \epsilon_{i,t}.
\end{aligned} \tag{1.6}
$$

In the above regression, *Ln(Seasoned CEOs Added)* is the natural log of one plus the number of managers added to the management team who have prior working experience as a CEO or president in another company. *Ln(Tech Mgrs Added)* is the natural log of one plus of the number of managers with a prior technical background that have been added to the management team. I include the indicator variable for adding new managers (*Add(Dummy)*) so that the coefficients on *Ln(Seasoned CEOs Added)* and on *Ln(Tech Mgrs Added)* capture the incremental effects of adding seasoned CEOs and adding managers with a prior technical background compared to the case of adding managers with other backgrounds. The results for the above regressions are reported in Table 8. I find that adding seasoned CEOs or presidents has a significantly positive effect on the firm's innovation, especially on the quality of innovation. However, adding managers with a prior technical background does not have a significant impact on innovation. The differences between the coefficients on *Ln(Seasoned CEOs Added)* and those on *Ln(Tech Mgrs Added)* are statistically significant at the 10% level for the regressions using the quality of innovation as the dependent variables. Collectively, these findings suggest that the new management teams enhance innovation in venture-backed entrepreneurial firms as they are better at managing resources and human capital, which support my hypothesis **H5** but not **H6**.

1.4.6 The Effect of Top Management Changes on Corporate Innovation in Different Development Stages

The level of risks faced by venture-backed firms in generating innovation as well as in running their business as a whole varies in different stages. In general, these venture-backed entrepreneurial firms face larger risks in their early stages than in their late stages when they mature. If top management changes do play a significant role in spurring innovation in venture-backed firms as documented earlier, I would expect the positive effect of top management changes on innovation to be stronger in a firm's early stages than in its late stages.

I estimate regression (1.1) for venture-backed companies in their early stages and in their late stages separately, where *Early Stage* includes "early stage" and "start-up/seed" stages and *Late Stage* includes the "later stage," "acquisition," "expansion," and "acquisition for expansion" stages. I report these results in Panel A of 9 use patent counts and patent citations as the dependent variables, respectively. I find that the effects of management changes on future innovation for ventures in their early stages are all positive and significant (mostly at the 1% level), while the marginal effects in their late stages are all insignificant. The differences of the coefficients on *Mgmt Change* in the early stage group and in the late stage group are significant mostly at the 10% level. To summarize, my findings support the conjecture that the marginal effect of management changes on innovation is stronger for venture-backed firms in their early stages when they face greater level of risks and difficulties running their businesses than in their late stages when they mature into development.

In Panel B, I investigate the effects of adding new managers as well as removing existing managers on innovation for ventures in the early stages and in the late stages by separately estimating the regressions using *Add Only*, *Remove Dummy*, and *Both* as the main explanatory variables across the above two groups. I find that the effects of adding new managers on future innovation are significantly positive and significantly larger (all at the 5% level) for ventures in their early stages than for ventures in their late stages, while the effects of removing existing managers on innovation for ventures in the early stages are not significant and not statistically different from those for ventures in the late stages. These results are also consistent with my earlier findings that adding new blood to the top management team is the major drive that enhances innovation.

1.4.7 Mechanism: Inventor Mobility Channel

My evidence so far is consistent with the notion that top management changes in venture-backed firms are likely to be driven by VCs and have positive impacts on future corporate innovation. In this section, I investigate the possible underlying mechanism through which this occurs. As argued earlier, the new management teams may select and allocate resources to higher quality innovation projects, manage innovative assets better, and provide a better environment for inventors (scientists and engineers) to succeed (for example, in the sense of Manso (2011), by creating a more failure-tolerant environment for inventors), all of which may make the firm more attractive to inventors. Thus, one way that management changes may enhance innovation is by being able to hire more inventors to work for the firm (after controlling for the size of investment). To assess the relationship between management changes and the movement of mobile inventors, I test the the following models:

$$Dep\ Var = \alpha + \beta Mgmt\ Change_{i,t} + \gamma Z_{i,t} + Industry \times Year + Stage + Round + \epsilon_{i,t}, \quad (1.7)$$

where i indexes firm and t indexes time and N equals two or three. The dependent variables for regression (1.7) are the two-year (or three-year) net inflow, outflow, and inflow of mobile inventors that have worked for different firms over my sample period of 2002-2010, respectively, which are defined as in Section 1.3.4. Z is vector of control variables used in prior tests. I include industry-by-year fixed effects to absorb the industry-wide technology shock that may affect the labor markets. I further include financing round fixed effects to account for the possibility that inventors may likely to move to a firm after it obtained VC financing.

Table 10 reports the results for the above regressions. Columns (1)-(3) correspond to regressions using the net inflow, inflow, and outflow of mobile inventors within two years following management changes as the dependent variables, respectively. Columns (4)-(6) use dependent variables that are measured within three years following management changes. Columns (1) and (2) as well as Columns (4) and (5) in Table 10 suggest that management changes are associated with a significantly greater net inflow and inflow of inventors following top management changes; while the association between management changes and the outflow of inventors is much smaller and insignificant. The economic magnitude of the effects of management changes on the net inflow and inflow of inventors is significant as well: for example, Column (1) suggests that top management changes are associated with a 5.7% increase in the net inflow of inventors over the next two years; and Column (4) suggests that top management changes are associated with associated with a 6.2% increase in the net inflow of inventor over the next three years. These findings support my hypothesis **H7**, and suggest that one mechanism through which top management changes enhance corporate innovation is by the new management team attracting more inventors to work for the firms (after controlling for the size of VC investment).

As argued in prior sections, if VCs have more power in the firm, they may be more effective in using top management changes to create value for the firm through the inventor mobility channel. Therefore, I would expect management changes to have a stronger effect on the net inflows of inventors for firms where VCs have greater power. To test this implication, I include the interaction term of management changes and an indicator variable for greater VC power in the above regressions and report the results for these tests in Panel B of Table 10. As shown in Columns (1) and (4), the coefficients on the interaction of *Mgmt Change* and *High Power* are significantly positive, suggesting that the effect of management changes on the net inflow of inventors is especially stronger for firms where VCs have greater power. Further, the effect of management changes on the future inflow of inventors is more pronounced in such firms, while the effect of management changes on the outflow of inventors is insignificant. Overall, my results are consistent with the conjecture that VCs are more effective in using top management changes to enhance innovation through attracting more inventors when they have more power in the firm.

1.4.8 The Effect of Top Management Changes and Corporate Innovation on Successful Exits

My results thus far have documented a positive relation between top management changes and subsequent corporate innovation. In this section, I investigate the implication of top management changes and corporate innovation on the successful exit of venture-backed firms. Both IPOs and acquisitions are considered as successful exit outcomes in the existing literature (e.g., Hochberg, Ljungqvist, and Lu (2007), Sörensen (2007), and Nahata (2008)). I therefore use the following variables to measure the successful exit of venture-backed firms: (i) *IPO*, a dummy variable equal to one if the venture-backed firm went public within ten years after receiving the first round of VC financing and zero otherwise; (ii) *MA*, a dummy variable equal to one if the venture-backed firm was acquired by another company within ten years after receiving the first round of VC financing and zero otherwise; (iii) *Exit*, a dummy variable equal to one if the venture-backed firm either went public or was acquired by another company within ten years after receiving the first round of VC financing.[26] In my sample, 5% of the venture-backed firms exited through an IPO and 21% of them exited through an acquisition. These statistics are comparable to those documented in the existing literature (e.g., Tian (2011) and Ewens and Marx (2014)). Using the above three measures as the dependent variables, I conduct the following firm-level probit regressions:

$$\begin{aligned} Prob(\mathit{Successful\ Exit}) = \alpha + \beta_1 Ln(Total\ Added) + \beta_2 Ln(Total\ Removed) \\ + \theta Ln(Innovation) + \gamma Z + Industry + \epsilon_i. \end{aligned} \tag{1.8}$$

[26] I require an IPO or acquisition to occur within ten years after the first VC financing, as most VC funds typically have a limited life of ten years (although with the possibility of a few years' extension).

In the above regression, *Ln(Total Added)* and *Ln(Total Removed)* are two different measures for top management changes at the firm level, which are defined as the natural log of one plus the total number of managers that have been added to the management team and the natural log of one plus the total number of managers that have been removed from the management team up to the last financing round, respectively. *Ln(Innovation)* is *Ln(Total Patents)* or *Ln(Total Citations)*, which are defined as the natural log of one plus the total number of patents filed by a firm and the natural log of one plus the total adjusted number of citations received by the patents filed by the firm up to the last financing round, respectively. Z is a set of control variables that may affect the exit outcome of venture-backed firms as suggested in the literature, which includes *Ln(VC Investment)* (the natural log of the total investment made by VCs), *Ln(Age)* (the natural log of a firm's age in the last VC financing round), and *VC Syndication* (a dummy variable equal to one if a firm receives VC funding from more than one VC firm at least for one financing round and zero otherwise). I also include industry fixed effects in the above regressions and use robust standard errors.

Table 11 reports the results for the above regressions. Columns (1)-(3) reports the effect of management changes and corporate innovation output on the probability of a venture-backed private firm going public within ten years of receiving the first VC financing round. The regression in Column (1) uses management change measures only as the main explanatory variables. I find that the coefficient on *Ln(Total Added)* is positive and significant, while the coefficient on *Ln(Total Removed)* is insignificant, suggesting that adding new managers has an important impact on the probability of a venture-backed private firm going public. In terms of economic magnitude, Column (1) suggests that a one standard deviation increase in *Ln(Total Added)* is associated with 2.4% increase in the probability of IPO. In the regressions in Columns (2) and (3), I include the patent counts and patent citations as additional explanatory variables, respectively. I find that the both coefficients on patent counts and patent citations are positive and significant at the 5% level. Further, the coefficient on *Ln(Total Added)* becomes less significant and smaller once the innovation variables are included. These results suggest the positive effect of management changes on IPO is likely to be at least partly mediated through enhanced innovation output. In terms of economic magnitude, Columns (2) suggests that a one standard deviation increase in the number of managers added is associated with 2.1% increase in the probability of a venture-backed firm's IPO and a one standard deviation increase in patent counts is associated with 1.6% increase in the probability of IPO. These results also suggest that management changes and corporate innovation have equally important impacts on the probability of an IPO, which is considered as a "gold standard" of venture success.

As reported in Columns (4)-(6), I find that patent counts and patent citations remain significant determinants of the probability of venture-backed firms getting acquired, while neither adding managers nor removing existing managers has a significant effect. In Columns (7)-(9), I find that adding new managers is positively and significantly associated with the probability of a venture-backed firm's exit either through a IPO or an acquisitions. Again, when innovation variables are included, the coefficients on the *Ln(Total Added)* become insignificant, suggesting that the effect of adding new managers on a firm's successful exit is at least partly mediated through innovation. These results suggest that both top management changes (especially adding new blood to the management team) and corporate innovation have a positive impact on the successful exit of venture-backed private firms. Collectively, these results support my hypotheses **H8** and **H9**.

1.5 Robustness Tests

1.5.1 Robustness to Controlling for Industry-by-State-by-Year Fixed Effects

Since my instrumental variable analysis makes use of variation at the industry-by-state-by-year level, one concern may be that that industry-by-state-by-year level omitted variables (e.g, a technology shock specific to some states) may affect both management changes and corporate innovation. To alleviate such concerns, I replace the industry and year fixed effects in the baseline models by industry-by-state-by-year fixed effects and re-run these regressions. I report the results for theses regressions in Table 12. For almost all the specifications, I find that the positive effect of management changes on future innovation remains positive and significant, even after controlling for the industry-by-state-by-year fixed effects. The economic magnitude remains significant as well: for example, three-year patent counts increase by 13.3% following management changes, and three-year patent citations increase by 15.2% following top management changes.

1.5.2 Placebo Test: The Effect of Top Management Changes on Corporate Innovation Generated Prior to Management Changes

To further alleviate the concern that the positive relationship between top management changes and enhanced innovation may be driven by some omitted variables such as a trend of technological development, I therefore conduct a placebo test using a firm's corporate innovation output generated prior to management changes as the dependent variables in this section. If enhanced innovation is indeed caused by management changes rather than drivers such as a trend of technological development, I would expect that management changes to have a significant effect only on innovation generated after management changes, but not on that generated prior to management changes. To test these implications, I estimate the following model:

$$Innovation^{(-N)} = \alpha + \beta Mgmt\ Change_{i,t} + \gamma Z_{i,t} + Industry + Year + Stage + \epsilon_{i,t}, \quad (1.9)$$

where $Innovation^{(-N)}$ includes $Patents^{(-N)}$ and $Cites^{(-N)}$, which are defined as the natural log of one plus the number of patents filed in the past N years prior to management changes and the natural log of one plus the total number of citations received by these patents, and N equals 2 and 3. The same set of control variables and fixed effects as in my baseline model (regression (1.1)) are included in the above models.

I present the results for the above placebo test in Table 13. For all the specifications, top management changes do not have a significant impact on innovation generated prior to top management changes. To summarize, the above results for the placebo test suggest that the positive relation between management changes and enhanced innovation is unlikely to be driven by omitted variables such as a trend of technological development.

1.5.3 Robustness to Controlling for Lead VC Firm Fixed Effects

Prior literature (e.g., Tian and Wang (2014)) has suggested that VC firm characteristics may affect its project selection ability or preferences and thus the characteristics and quality of the projects that it funded. To alleviate the concern that the relation between management changes and corporate innovation may be driven by VC firm characteristics, I include lead VC firm fixed effects in my baseline models in this section.[27] This helps to control for the effect of any unobservable and time-invariant VC characteristics. If the VC firm's project selection ability or preference (as reflected in the project quality) has a time-invariant component, then including lead VC firm fixed effects will mitigate this impact.

The results of this test are reported in Table 14. Consistent with my earlier results, the coefficients on management changes are significantly positive for almost all the specifications, even after controlling for the lead VC firm fixed effects. This suggests that the positive relation between management changes and enhanced future innovation is not likely to be driven by the unobservable characteristics of VC firms such as project selection ability or preferences.

1.6 Conclusion

Using a unique hand-collected dataset, I analyze the effect of top management changes on corporate innovation in venture-backed private firms. This is the first paper to establish the causal link between top management changes as a specific action by venture capitalists and

[27] Following the existing literature (e.g., Hochberg, Ljungqvist, and Lu (2007)), I define the lead VC as the one that makes the largest total investment across all rounds of funding in a venture-backed firm.

product market innovations of their portfolio companies. I find that top management changes are associated with significantly more and higher quality corporate innovation output. Further, my evidence suggests that top management changes in venture-backed private firms are likely to be driven by venture capitalists and that the effect of management changes on innovation is stronger for firms where venture capitalists have more power. These results are consistent with the existing studies suggesting that venture capitalists provide value-addition services beyond providing capital for their portfolio companies through active intervention in recruiting management (see, e.g., Gorman and Sahlman (1989) and Hellmann and Puri (2002)). An instrumental variable analysis making use of a plausibly exogenous shock to the supply of outside managers shows that the above documented relation is causal.

My evidence also suggests that adding new managers has a positive and significant effect on enhancing innovation, while removing existing managers does not. Having established that, I use hand-collected information on educational background and employment history of each new manager and find that adding seasoned CEOs or presidents to the firm's top management team (not necessarily as a CEO or president) has a positive and significant effect on innovation, while adding senior managers with a prior technical background does not. Further, I analyze the possible underlying mechanisms through which top management changes may affect corporate innovation in venture-backed private firms and establish that one such mechanism is through new management teams hiring a greater number of inventors and scientists for a given investment size. Finally, I find that top management changes have a positive effect on the probability of a firm's successful exit (especially exit via an IPO) and such an effect is at least partly through enhanced innovation.

References

Amornsiripanitch, Natee, Paul A. Gompers, and Yuhai Xuan, 2016, More than money: Venture capitalists on boards, Working paper, Havard Business School.

Bereskin, Frederick L., and Po-Hsuan Hsu, 2013, Bringing in changes: The effect of new ceos on innovation, Working paper, University of Delaware.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend, 2015, The impact of venture capital monitoring, *The Journal of Finance (Forthcoming)* .

Bishara, Norman D., Kenneth J. Martin, and Randall S. Thomas, 2015, An empirical analysis of noncompetition clauses and other restrictive postemployment covenants, *Vanderbilt Law Review* 68, 1–51.

Boot, Arnoud W. A., 1992, Why hang on to losers? divestitures and takeovers, *The Journal of Finance* 47, 1401–1423.

Chemmanur, Thomas J., Lei Kong, Karthik Krishnan, and Qianqian Yu, 2016, Top management human capital, inventor mobility, and corporate innovation, Working paper, Boston College.

Chemmanur, Thomas J., Karthik Krishnan, and Debarshi K. Nandy, 2011, How does venture capital financing improve efficiency in private firms? a look beneath the surface, *Review of Financial Studies* 24, 4037–4090.

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

Cornelli, Francesca, and Oğuzhan Karakaş, 2015, CEO turnover in LBOs: The role of boards, Working paper, LBS.

Cornelli, Francesca, Zbigniew Kominek, and Alexander Ljungqvist, 2013, Monitoring managers: Does it matter?, *The Journal of Finance* 68, 431–481.

Da Rin, Marco, Thomas F. Hellmann, and Manju Puri, 2013, A survey of venture capital research, in George M. Constantinides, Milton Harris, and René M. Stulz, eds., *Handbook of the Economics of Finance*, 573–648 (Elsevier, Amsterdam).

Denis, David J., and Diane K. Denis, 1995, Performance changes following top management dismissals, *The Journal of Finance* 50, 1029–1057.

Ewens, Michael, and Matt Marx, 2014, Executive replacement in venture capital-backed startups, Working paper, Caltech.

Gao, Huasheng, Jarrad Harford, and Kai Li, 2015, CEO turnover-performance sensitivities in private firms, *The Journal of Financial and Quantitative Analysis (Forthcoming)* .

Garmaise, Mark J., 2009, Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment, *Journal of Law, Economics, and Organization* 376–425.

Gorman, Michael, and William A. Sahlman, 1989, What do venture capitalists do?, *Journal of Business Venturing* 4, 231–248.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working Paper 8498, National Bureau of Economic Research.

Hellmann, Thomas, and Manju Puri, 2002, Venture capital and the professionalization of start-up firms: Empirical evidence, *The Journal of Finance* 57, 169–197.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *The Journal of Finance* 62, 251–301.

Huang, Sheng, 2014, Managerial expertise, corporate decisions and firm value: Evidence from corporate refocusing, *Journal of Financial Intermediation* 23, 348–375.

Huson, Mark R., Robert Parrino, and Laura T. Starks, 2001, Internal monitoring mechanisms and ceo turnover: A long-term perspective, *The Journal of Finance* 56, 2265–2297.

Kaplan, Steven N., and Per Strömberg, 2003, Financial contracting theory meets the real world: An empirical analysis of venture capital contracts, *The Review of Economic Studies* 70, 281–315.

Knyazeva, Anzhela, Diana Knyazeva, and Ronald W. Masulis, 2013, The supply of corporate directors and board independence, *Review of Financial Studies* 26, 1561–1605.

Lerner, Josh, 1995, Venture capitalists and the oversight of private firms, *The Journal of Finance* 50, 301–318.

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

Malsberger, Brian M., 2004, *Covenants Not To Compete: A State-by-state Survey* (Bna Books, Washington).

Manso, Gustavo, 2011, Motivating innovation, *The Journal of Finance* 66, 1823–1860.

Marx, Matt, Deborah Strumsky, and Lee Fleming, 2009, Mobility, skills, and the michigan non-compete experiment, *Management Science* 55, 875–889.

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

Oyer, Paul, and Scott Schaefer, 2011, Chapter 20 - personnel economics: Hiring and incentives, volume 4, Part B of *Handbook of Labor Economics*, 1769–1823 (Elsevier).

Pan, Yihui, 2015, The determinants and impact of executive-firm matches, *Management Science (Forthcoming)* .

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

Sörensen, Morten, 2007, How smart is smart money? a two-sided matching model of venture capital, *The Journal of Finance* 62, 2725–2762.

Stock, James H., and Motohiro Yogo, 2005, Testing for weak instruments in linear IV regression, *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* .

Tian, Xuan, 2011, The role of venture capital syndication in value creation for entrepreneurial firms, *Review of Finance* 245–283.

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

Wasserman, Noam, 2003, Founder-CEO succession and the paradox of entrepreneurial success, *Organization Science* 14, 149–172.

Weisbach, Michael S., 1988, Outside directors and CEO turnover, *Journal of Financial Economics* 20, 431–460, The Distribution of Power Among Corporate Managers, Shareholders, and Directors.

Weisbach, Michael S., 1995, CEO turnover and the firm's investment decisions, *Journal of Financial Economics* 37, 159–188.

Wooldridge, Jeffrey M., 2010, *Econometric analysis of cross section and panel data*, second edition (MIT press., Cambridge).

Table 1: Summary Statistics

This table reports the summary statistics for my sample of venture-backed private firms between 2002 and 2010. *Patents*$^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; *Patents*$^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; *Cites*$^{(2)}$is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; *Cites*$^{(3)}$is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Management Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *Add (Dummy)* is a dummy variable equal to one for a firm-financing round if new managers were added to the top management team and zero otherwise; *Remove (Dummy)* is a dummy variable equal to one if existing managers were removed from the top management team and zero otherwise. *Add (Fraction)* is the number of new managers added to the top management team divided by the total number of managers on the top management team for a firm-financing round; *Remove (Fraction)* is the number of existing managers removed from the top management team divided by the total number of managers on the top management team. *Add (Raw Number)* is the number of new managers added to the top management team for a firm-financing round; *Remove (Raw Number)* is the number of existing managers removed from the top management team for a firm-financing round. *Ln(VC Investment)* is the natural log of VC investment amount. *Syndicate Size* is the number of investing VCs. *Management Team Size* is the total number of managers on the top management team. *Outside Board Members* is the number of outside board members. *Firm Age* is the age of the venture-backed firm in the financing year since it was founded.

Variable	N	Mean	Stdev	Min	P25	Median	P75	Max
Patents$^{(2)}$	977	0.503	0.801	0.000	0.000	0.000	0.693	3.738
Patents$^{(3)}$	977	0.606	0.911	0.000	0.000	0.000	1.099	3.829
Cites$^{(2)}$	977	0.401	0.800	0.000	0.000	0.000	0.327	4.036
Cites$^{(3)}$	977	0.484	0.906	0.000	0.000	0.000	0.693	4.325
Management Change	977	0.306	0.461	0.000	0.000	0.000	1.000	1.000
Add (Dummy)	977	0.230	0.421	0.000	0.000	0.000	0.000	1.000
Remove (Dummy)	977	0.166	0.372	0.000	0.000	0.000	0.000	1.000
Add (Fraction)	977	0.110	0.214	0.000	0.000	0.000	0.000	0.833
Remove (Fraction)	977	0.122	0.370	0.000	0.000	0.000	0.000	1.000
Add (Raw Number)	977	0.410	0.991	0.000	0.000	0.000	0.000	15.000
Remove (Raw Number)	977	0.257	0.705	0.000	0.000	0.000	0.000	8.000
Ln(VC Investment)	977	8.478	1.230	3.664	7.730	8.613	9.306	12.367
Syndicate Size	977	3.230	1.957	1.000	2.000	3.000	4.000	15.000
Management Team Size	977	2.595	1.615	1.000	2.000	2.000	3.000	18.000
Outside Board Members	977	3.117	1.700	0.000	2.000	3.000	4.000	9.000
Firm Age	977	3.070	2.707	0.000	1.000	3.000	4.000	26.000

Table 2: The Effect of Top Management Changes on Corporate Innovation (Baseline Results)

This table reports the OLS regression results of corporate innovation on top management changes. *Patents*$^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; *Patents*$^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; *Cites*$^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; *Cites*$^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Mgmt Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry fixed effects (defined at the 2-digit SIC code level), financing year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Patents$^{(2)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(3)}$
Mgmt Change	0.140***	0.116**	0.117**	0.080
	(0.048)	(0.056)	(0.047)	(0.062)
Ln(VC Investment)	0.169***	0.197***	0.160***	0.179***
	(0.035)	(0.044)	(0.034)	(0.042)
Ln(Syndicate Size)	0.074	0.074	0.058	0.023
	(0.070)	(0.072)	(0.076)	(0.085)
Ln(Mgmt Team Size)	-0.052	0.054	-0.049	0.037
	(0.074)	(0.110)	(0.084)	(0.127)
Observations	743	577	743	577
Adjusted R-squared	0.195	0.177	0.165	0.132
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 3: The Effect of VC Power on the Probability of Top Management Changes

This table reports the probit regression results of the probability of top management changes on measures for VC power. *Mgmt Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *Ln(Outside Board Members)* is the natural log of one plus the number of outside board members. *Fraction of Outside Board Members* is the number of outside board members divided by the total number of board members. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. *Ln(Firm Age)* is the natural log of one plus the firm's age in the financing year since it was founded. Intercept, 2-digit SIC industry fixed effects, financing year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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	Mgmt Change	Mgmt Change
Ln(Outside Board Members)	0.645***	
	(0.185)	
Fraction of Outside Board Members		1.472***
		(0.361)
Ln(VC Investment)	-0.018	-0.021
	(0.037)	(0.034)
Ln(Syndicate Size)	0.241***	0.298***
	(0.093)	(0.092)
Ln(Mgmt Team Size)	0.945***	1.088***
	(0.105)	(0.110)
Ln(Firm Age)	-0.234***	-0.235***
	(0.077)	(0.071)
Observations	955	955
Pseudo R-squared	0.264	0.256
Industry FE	Yes	Yes
Year FE	Yes	Yes
Stage FE	Yes	Yes

Table 4: The Effect of Top Management Changes on Corporate Innovation for Firms with Different VC Power

This table reports the OLS regression results of corporate innovation on the interaction between top management changes and a dummy variable for greater VC power. *Patents*$^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; *Patents*$^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; *Cites*$^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; *Cites*$^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Mgmt Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *High Power* is a dummy variable equal to one if the number of outside board members is above the sample median and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry fixed effects, financing year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Patents$^{(2)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(3)}$
Mgmt Change × High Power	0.179***	0.357***	0.158**	0.333***
	(0.052)	(0.084)	(0.075)	(0.100)
Mgmt Change	0.055	-0.076	0.041	-0.096
	(0.057)	(0.093)	(0.071)	(0.088)
High Power	-0.114	-0.151	-0.097	-0.158
	(0.084)	(0.134)	(0.087)	(0.128)
Ln(VC Investment)	0.171***	0.193***	0.161***	0.176***
	(0.037)	(0.047)	(0.035)	(0.044)
Ln(Syndicate Size)	0.083	0.086	0.066	0.036
	(0.072)	(0.072)	(0.079)	(0.086)
Ln(Mgmt Team Size)	-0.047	0.078	-0.044	0.059
	(0.074)	(0.110)	(0.087)	(0.130)
Observations	743	577	743	577
Adjusted R-squared	0.196	0.180	0.165	0.134
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 5: The Effect of Top Management Changes on Corporate Innovation: Instrumental Variable Analysis

Panel A of this table reports the Instrumental Variable (IV/2SLS) regression results of corporate innovation on top management changes. The instrumental variable used is the number of acquisitions made by public firms in the same industry and in the same state as the venture-backed firm multiplied by an index measuring the enforceability of non-compete clauses in that state. Column (1) reports the first-stage probit regression result, i.e., regressing the probability of top management changes on the instrumental variable and other controls. Columns (2)-(5) reports the second-stage results of the IV regressions using the number of patents and total number of citations in the next two and three years as dependent variables, respectively. Panel B reports the second-stage results of the IV regressions for the relation between top management changes, VC power, and corporate innovation. $Patents^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; $Patents^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; $Cites^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; $Cites^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. *Ln(Outside Board Members)* is the natural log of one plus the number of outside board members. *Ln(Firm Age)* is the natural log of one plus the firm's age in the financing round since it was founded. Intercept, industry by year fixed effects, state by year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the industry 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 Top Management Changes on Corporate Innovation (2SLS Results)

	(1)	(2)	(3)	(4)	(5)
	1st-Stage	2SLS			
VARIABLES	Mgmt Change	Patents$^{(2)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(3)}$
Instrument	0.005***				
	(0.001)				
Mgmt Change		0.392***	0.579***	0.487**	0.689***
		(0.127)	(0.159)	(0.203)	(0.238)
Ln(VC Investment)	-0.081	0.177***	0.205***	0.181***	0.204***
	(0.129)	(0.033)	(0.034)	(0.034)	(0.042)
Ln(Syndicate Size)	0.410*	0.147	0.082	0.093	-0.044
	(0.248)	(0.103)	(0.132)	(0.129)	(0.156)
Ln(Mgmt Team Size)	1.062***	-0.001	0.039	-0.033	-0.014
	(0.146)	(0.068)	(0.077)	(0.081)	(0.109)
Ln(Outside Board Members)	1.308**	-0.028	0.033	-0.123	-0.037
	(0.539)	(0.077)	(0.097)	(0.075)	(0.090)
Ln(Firm Age)	-0.648***	0.014	-0.009	-0.044	-0.086
	(0.170)	(0.066)	(0.097)	(0.050)	(0.090)
Observations	743	743	577	743	477
Pseudo R-squared	0.367				
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes

Panel B: The Effect of Top Management Changes on Corporate Innovation for Firms with Different VC Power (2SLS Results)

	(1)	(2)	(3)	(4)
VARIABLES	$Patents^{(2)}$	$Patents^{(3)}$	$Cites^{(2)}$	$Cites^{(3)}$
Mgmt Change × High Power	0.407***	0.476***	0.515***	0.564***
	(0.118)	(0.110)	(0.133)	(0.180)
Mgmt Change	0.086	0.252	0.119	0.314
	(0.159)	(0.176)	(0.219)	(0.290)
High Power	-0.030	-0.143	-0.096	-0.199
	(0.060)	(0.113)	(0.100)	(0.175)
Ln(VC Investment)	0.169***	0.199***	0.173***	0.197***
	(0.030)	(0.031)	(0.032)	(0.040)
Ln(Syndicate Size)	0.135	0.071	0.078	-0.057
	(0.097)	(0.129)	(0.124)	(0.158)
Ln(Mgmt Team Size)	0.072	0.083	0.034	0.027
	(0.082)	(0.089)	(0.085)	(0.132)
Ln(Outside Board Members)	-0.048	0.064	-0.120	0.012
	(0.093)	(0.112)	(0.112)	(0.124)
Ln(Firm Age)	0.007	-0.006	-0.051	-0.082
	(0.067)	(0.104)	(0.053)	(0.100)
Observations	743	577	743	577
Industry-by-Year FE	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 6: The Effect of Adding and Removing Managers on Corporate Innovation

This table reports the OLS regression results of corporate innovation on adding new managers to and removing existing managers from the top management team. Panel A uses three separate dummy variables for adding new managers only, removing managers only, and both adding and removing managers, as the main explanatory variables. Panel B uses the fraction and number of managers added and removed as the main explanatory variables. $Patents^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; $Patents^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; $Cites^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; $Cites^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Add Only* is a dummy variable equal to one if new managers were added to the management team for a firm-round and no existing managers were removed, and zero otherwise; *Remove Only* is a dummy variable equal to one if existing managers were removed from the management team for a firm-round but no new managers were added, and zero otherwise; *Both* is a dummy variable equal to one if new managers were added to and existing managers were removed from a firm's management team as well for a firm-round observation, and zero otherwise. *Add (Fraction)* is the number of new managers added to the top management team divided by the total number of managers on the top management team for a firm-financing round; *Remove (Fraction)* is the number of existing managers removed from the top management team divided by the total number of managers on the top management team. *Add (Log Number)* is the natural log of one plus the number of new managers added to the top management team for a firm-financing round; *Remove (Log Number)* is the natural log of one plus the number of existing managers removed from the top management team. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry fixed effects, financing year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the industry 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 Adding and Removing Managers on Innovation

	(1)	(2)	(3)	(4)
VARIABLES	Patents$^{(2)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(3)}$
Add Only	0.225**	0.175**	0.200**	0.140
	(0.086)	(0.080)	(0.097)	(0.098)
Both	0.117*	0.105*	0.029	0.028
	(0.061)	(0.060)	(0.098)	(0.095)
Remove Only	0.127	0.107	0.123	0.103
	(0.107)	(0.106)	(0.129)	(0.159)
Ln(VC Investment)	0.158***	0.197***	0.144***	0.170***
	(0.031)	(0.038)	(0.027)	(0.035)
Ln(Syndicate Size)	0.029	0.013	0.016	-0.049
	(0.084)	(0.089)	(0.089)	(0.101)
Ln(Mgmt Team Size)	-0.086	-0.004	-0.076	-0.024
	(0.056)	(0.084)	(0.067)	(0.079)
Observations	743	577	743	577
Adjusted R-squared	0.298	0.308	0.259	0.259
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Panel B: Using Alternative Measures for Adding and Removing Managers

	(1)	(2)	(3)	(4)
VARIABLES	Patents$^{(2)}$	Cites$^{(2)}$	Patents$^{(2)}$	Cites$^{(2)}$
Add (Fraction)	0.313***	0.253*		
	(0.112)	(0.147)		
Remove(Fraction)	0.066	0.049		
	(0.062)	(0.079)		
Add(Log Number)			0.169**	0.129*
			(0.063)	(0.078)
Remove(Log Number)			0.064	0.036
			(0.113)	(0.129)
Ln(VC Investment)	0.159***	0.146***	0.160***	0.147***
	(0.031)	(0.029)	(0.032)	(0.029)
Ln(Syndicate Size)	0.030	0.015	0.028	0.014
	(0.082)	(0.088)	(0.083)	(0.091)
Ln(Mgmt Team Size)	-0.070	-0.069	-0.105*	-0.092
	(0.052)	(0.062)	(0.057)	(0.061)
Observations	743	743	743	743
Adjusted R-squared	0.297	0.258	0.298	0.258
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 7: The Effect of Adding and Removing Managers on Corporate Innovation for Firms with Different VC Power

This table reports the OLS regression results of corporate innovation on the interaction between measures for adding and removing managers and a dummy variable for greater VC power. $Patents^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; $Patents^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; $Cites^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; $Cites^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *High Power* is a dummy variable equal to one if the number of outside board members is above the sample median and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Add Only* is a dummy variable equal to one if new managers were added to the management team for a firm-round and no existing managers were removed, and zero otherwise; *Remove Only* is a dummy variable equal to one if existing managers were removed from the management team for a firm-round but no new managers were added, and zero otherwise; *Both* is a dummy variable equal to one if new managers were added to and existing managers were removed from a firm's management team as well for a firm-round observation, and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. All standard errors are adjusted for clustering at the 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) Patents$^{(2)}$	(2) Patents$^{(3)}$	(3) Cites$^{(2)}$	(4) Cites$^{(3)}$
Add Only × High Power	0.345**	0.393**	0.278*	0.306
	(0.159)	(0.189)	(0.169)	(0.204)
Both × High Power	0.136	0.285	0.183	0.402*
	(0.219)	(0.271)	(0.221)	(0.228)
Remove Only × High Power	-0.130	0.371	-0.163	0.189
	(0.193)	(0.351)	(0.244)	(0.362)
Add Only	0.011	-0.063	0.043	-0.032
	(0.097)	(0.127)	(0.094)	(0.128)
Both	-0.007	-0.109	-0.100	-0.261
	(0.144)	(0.201)	(0.151)	(0.189)
Remove Only	0.283	-0.066	0.288	0.076
	(0.190)	(0.333)	(0.225)	(0.336)
High Power	-0.116	-0.151	-0.100	-0.157
	(0.084)	(0.134)	(0.086)	(0.128)
Ln(VC Investment)	0.171***	0.191***	0.160***	0.173***
	(0.037)	(0.046)	(0.035)	(0.042)
Ln(Syndicate Size)	0.086	0.088	0.070	0.039
	(0.072)	(0.071)	(0.078)	(0.086)
Ln(Mgmt Team Size)	-0.052	0.080	-0.045	0.064
	(0.085)	(0.124)	(0.100)	(0.138)
Observations	743	577	743	577
Adjusted R-squared	0.195	0.175	0.165	0.129
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 8: The Effect of Management Team Background on Corporate Innovation

This table reports the effects of adding seasoned CEOs and adding managers with a prior technical background on corporate innovation. $Patents^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; $Patents^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; $Cites^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; $Cites^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Ln(Seasoned CEOs Added)* is the natural log of one plus the number of managers who have previously worked as CEOs or presidents in other companies added to the firm's management team. *Ln(Tech Mgrs Added)* is the natural log of one plus the number of managers with a prior technical background added to the firm's management team. *Add (Dummy)* is a dummy variable equal to one for a firm-financing round if new managers were added to the top management team and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry fixed effects, financing year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	$\text{Patents}^{(2)}$	$\text{Patents}^{(3)}$	$\text{Cites}^{(2)}$	$\text{Cites}^{(3)}$
Ln(Seasoned CEOs Added)	0.244*	0.303*	0.398**	0.497**
	(0.128)	(0.157)	(0.173)	(0.237)
Ln(Tech Mgrs Added)	-0.034	-0.089	-0.080	-0.128
	(0.139)	(0.201)	(0.128)	(0.178)
Add(Dummy)	0.122	0.087	0.050	-0.000
	(0.078)	(0.085)	(0.086)	(0.079)
Ln(VC Investment)	0.163***	0.200***	0.150***	0.174***
	(0.032)	(0.039)	(0.030)	(0.038)
Ln(Syndicate Size)	0.030	0.016	0.016	-0.047
	(0.086)	(0.095)	(0.091)	(0.104)
Ln(Mgmt Team Size)	-0.097*	-0.008	-0.082	-0.027
	(0.051)	(0.091)	(0.050)	(0.060)
Observations	743	577	743	577
Adjusted R-squared	0.298	0.310	0.263	0.266
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 9: The Effect of Top Management Changes on Corporate Innovation in Different Development Stages

Panel A of this table reports the OLS regression results of corporate innovation on top management changes in the early stages versus in the late stages. Panel B reports the effect of adding new managers as well as removing existing managers on corporate innovation in the early stages versus in the late stages. The tests results for the differences between coefficients on management changes in the early stages versus in the late stages are reported at the bottom of each panel. *Early Stage* includes "early stage" and "start-up/seed" stages. *Late Stage* includes the "later stage," "acquisition," "expansion," and "acquisition for expansion" stages. *Patents*$^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; *Patents*$^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; *Cites*$^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; *Cites*$^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Mgmt Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *Add Only* is a dummy variable equal to one if new managers were added to the management team for a firm-round and no existing managers were removed, and zero otherwise; *Remove Only* is a dummy variable equal to one if existing managers were removed from the management team for a firm-round but no new managers were added, and zero otherwise; *Both* is a dummy variable equal to one if new managers were added to and existing managers were removed from a firm's management team as well for a firm-round observation, and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry fixed effects, and financing year fixed effects are included in all regressions. All standard errors are adjusted for clustering at the industry 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 Top Management Changes on Innovation in Different Stages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Early	Late	Early	Late	Early	Late	Early	Late
VARIABLES	Patents$^{(2)}$	Patents$^{(2)}$	Patents$^{(3)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(2)}$	Cites$^{(3)}$	Cites$^{(3)}$
Mgmt Change (β)	0.212***	-0.061	0.233***	-0.097	0.197***	-0.038	0.179**	-0.015
	(0.052)	(0.132)	(0.066)	(0.210)	(0.054)	(0.160)	(0.078)	(0.194)
Ln(VC Investment)	0.168***	0.224***	0.183***	0.262***	0.175***	0.212***	0.184***	0.241***
	(0.043)	(0.038)	(0.056)	(0.071)	(0.046)	(0.050)	(0.057)	(0.082)
Ln(Syndicate Size)	-0.032	0.175*	-0.067	0.230	-0.068	0.151*	-0.138	0.169
	(0.083)	(0.091)	(0.084)	(0.156)	(0.088)	(0.083)	(0.108)	(0.143)
Ln(Mgmt Team Size)	-0.087	-0.044	0.036	0.018	-0.117	0.003	0.018	-0.010
	(0.115)	(0.106)	(0.155)	(0.187)	(0.151)	(0.140)	(0.198)	(0.203)
Observations	387	343	302	266	387	343	302	266
Adjusted R-squared	0.169	0.216	0.125	0.211	0.130	0.199	0.072	0.164
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dif between β	0.273*		0.330*		0.235*		0.193	

Panel B: The Effect of Adding and Removing Managers on Innovation in Different Stages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Early	Late	Early	Late	Early	Late	Early	Late
VARIABLES	Patents$^{(2)}$	Patents$^{(2)}$	Patents$^{(3)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(2)}$	Cites$^{(3)}$	Cites$^{(3)}$
Add Only (β_{add})	0.317***	-0.201	0.317***	-0.292	0.355***	-0.216	0.312***	-0.332
	(0.092)	(0.196)	(0.091)	(0.238)	(0.106)	(0.214)	(0.102)	(0.251)
Both	0.092	0.164	0.134	0.125	0.040	0.265	0.055	0.268
	(0.092)	(0.437)	(0.121)	(0.623)	(0.123)	(0.479)	(0.156)	(0.692)
Remove Only	0.190	0.087	0.207	0.226	0.138	0.144	0.096	0.541
	(0.160)	(0.172)	(0.194)	(0.360)	(0.187)	(0.221)	(0.244)	(0.364)
Ln(VC Investment)	0.168***	0.228***	0.182***	0.269***	0.176***	0.217***	0.185***	0.252***
	(0.044)	(0.037)	(0.057)	(0.069)	(0.046)	(0.052)	(0.058)	(0.083)
Ln(Syndicate Size)	-0.027	0.170*	-0.061	0.214	-0.062	0.145*	-0.130	0.143
	(0.083)	(0.088)	(0.090)	(0.147)	(0.090)	(0.077)	(0.117)	(0.133)
Ln(Mgmt Team Size)	-0.100	-0.040	0.022	0.024	-0.144	0.008	-0.017	0.005
	(0.146)	(0.100)	(0.186)	(0.187)	(0.185)	(0.136)	(0.233)	(0.198)
Observations	387	343	302	266	387	343	302	266
Adjusted R-squared	0.170	0.214	0.121	0.209	0.135	0.200	0.071	0.171
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dif between β_{add}	0.518**		0.610**		0.570**		0.644**	

Table 10: The Effect of Top Management Changes on Inventor Mobility

Panel A of this table reports the effect of top management changes on the net inflow, inflow, and outflow of mobile inventors. Panel B reports the effect of top management changes and VC power on the net inflow, inflow, and outflow of mobile inventors. *Inflow*$^{(N)}$ and *Outflow*$^{(N)}$ are defined as the natural log of one plus the total number of inventors that move in and that move out in the next N years following management change, where N equals 2 and 3. *Net Inflow*$^{(N)}$ is defined as the difference between the inflow and outflow of inventors as described above. *High Power* is a dummy variable equal to one if the number of outside board members is above the sample median and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry by year fixed effects, startup development stage fixed effects, and financing round fixed effects are included in all regressions. All standard errors are adjusted for clustering at the industry 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 Top Management Changes on the Net Inflow, Inflow, and Outflow of Inventors

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Net Inflow$^{(2)}$	Inflow$^{(2)}$	Outflow$^{(2)}$	Net Inflow$^{(3)}$	Inflow$^{(3)}$	Outflow$^{(3)}$
Mgmt Change	0.057***	0.056***	-0.001	0.062*	0.062*	-0.000
	(0.018)	(0.019)	(0.001)	(0.034)	(0.035)	(0.002)
Ln(VC Investment)	0.052**	0.055**	0.004	0.074***	0.079***	0.005
	(0.019)	(0.021)	(0.003)	(0.025)	(0.027)	(0.003)
Ln(Syndicate Size)	0.033	0.034	0.001	0.049	0.050	0.001
	(0.036)	(0.038)	(0.003)	(0.057)	(0.059)	(0.005)
Ln(Mgmt Team Size)	-0.024	-0.022	0.002	0.003	0.005	0.002
	(0.061)	(0.060)	(0.006)	(0.095)	(0.094)	(0.007)
Observations	743	743	743	577	577	577
Adjusted R-squared	0.112	0.139	0.201	0.129	0.152	0.195
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: The Effect of Top Management Changes and VC Power on the Net Inflow, Inflow, and Outflow of Mobile Inventors

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Net Inflow$^{(2)}$	Inflow$^{(2)}$	Outflow$^{(2)}$	Net Inflow$^{(3)}$	Inflow$^{(3)}$	Outflow$^{(3)}$
Mgmt Change × High Power	0.135***	0.113**	-0.022	0.124**	0.095	-0.029
	(0.039)	(0.046)	(0.024)	(0.057)	(0.064)	(0.031)
Mgmt Change	-0.027	-0.018	0.009	-0.027	-0.013	0.013
	(0.030)	(0.026)	(0.012)	(0.059)	(0.053)	(0.017)
High Power	-0.052	-0.052	-0.001	-0.038	-0.039	-0.001
	(0.037)	(0.038)	(0.004)	(0.051)	(0.053)	(0.005)
Ln(VC Investment)	0.051***	0.055***	0.004	0.072***	0.078***	0.006*
	(0.018)	(0.020)	(0.003)	(0.025)	(0.027)	(0.003)
Ln(Syndicate Size)	0.029	0.030	0.001	0.037	0.038	0.000
	(0.036)	(0.037)	(0.004)	(0.052)	(0.054)	(0.005)
Ln(Mgmt Team Size)	-0.015	-0.015	-0.000	0.013	0.012	-0.000
	(0.058)	(0.058)	(0.004)	(0.090)	(0.090)	(0.005)
Observations	743	743	743	577	577	577
Adjusted R-squared	0.119	0.143	0.209	0.133	0.153	0.204
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: The Effect of Top Management Changes and Corporate Innovation on the Successful Exit of Venture-Backed Private Firms

This table reports the firm-level probit regression results of the probability of the successful exit of venture-backed firms on top management changes and corporate innovation output generated up to the last financing round. *IPO* is a dummy variable equal to one if the firm exited via an initial public offering within ten years of the first financing round and zero otherwise. *MA* is a dummy variable equal to one if the venture-backed firm exited via an acquisition within ten years of the first financing round and zero otherwise. *Exit* is a dummy variable equal to one if the venture-backed firm exited via either an initial public offering or an acquisition within ten years of the first financing round and zero otherwise. *Ln(Total Added)* is the natural log of one plus the total number of managers that have been added to the firm's management team up to the last financing round. *Ln(Total Removed)* is the natural log of one plus the total number of managers that have been removed from the firm's management team up to the last financing round. *Ln(Total Patents)* is the natural log of one plus the total number of patents filed by the venture-backed firm up to the last financing round. *Ln(Total Citations)* is the natural log of one plus the adjusted total number of citations received by all the patents filed by the venture-backed firms up to the last financing round. *Ln(VC Investment)* is the natural log of the VC investment amount. *Ln(Age)* is the natural log of the age of the firm in the last VC financing round. *VC Syndication* is a dummy variable equal to one if a firm is backed by more than one VC firm in any financing round and zero otherwise. Intercept and industry fixed effects are included in all regressions. Robust standard errors are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	IPO	IPO	IPO	MA	MA	MA	Exit	Exit	Exit
Ln(Total Added)	0.470**	0.442*	0.443*	0.113	0.088	0.087	0.252*	0.223	0.222
	(0.237)	(0.236)	(0.236)	(0.144)	(0.144)	(0.145)	(0.138)	(0.139)	(0.139)
Ln(Total Removed)	-0.142	-0.146	-0.128	-0.112	-0.124	-0.119	-0.140	-0.154	-0.149
	(0.275)	(0.280)	(0.276)	(0.158)	(0.161)	(0.161)	(0.155)	(0.158)	(0.158)
Ln(Total Patents)		0.226**			0.156*			0.190**	
		(0.114)			(0.087)			(0.086)	
Ln(Total Citations)			0.208**			0.142**			0.178**
			(0.094)			(0.071)			(0.070)
Ln(VC Investment)	0.595***	0.569***	0.572***	0.194***	0.170**	0.174**	0.316***	0.286***	0.291***
	(0.177)	(0.182)	(0.182)	(0.068)	(0.070)	(0.070)	(0.071)	(0.072)	(0.072)
Ln(Age)	0.097	0.115	0.116	-0.013	-0.022	-0.019	0.025	0.018	0.021
	(0.106)	(0.106)	(0.105)	(0.097)	(0.098)	(0.098)	(0.089)	(0.089)	(0.088)
VC Syndication	-0.649	-0.633	-0.686	0.292	0.312	0.280	0.140	0.163	0.124
	(0.567)	(0.584)	(0.597)	(0.283)	(0.277)	(0.280)	(0.279)	(0.272)	(0.277)
Observations	422	422	422	422	422	422	422	422	422
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.256	0.279	0.284	0.054	0.061	0.063	0.078	0.086	0.091

Table 12: Robustness Test: Controlling for Industry-by-State-by-Year Fixed Effects

This table reports the OLS regression results of corporate innovation on top management changes controlling for industry-by-state-by-year fixed effects. *Patents*$^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; *Patents*$^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; *Cites*$^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; *Cites*$^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Mgmt Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry-by-state-by-year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Patents$^{(2)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(3)}$
Mgmt Change	0.137*	0.133**	0.119	0.152**
	(0.076)	(0.060)	(0.098)	(0.052)
Ln(VC Investment)	0.129***	0.191***	0.132***	0.172***
	(0.025)	(0.033)	(0.029)	(0.043)
Ln(Syndicate Size)	0.157	0.145	0.103	0.025
	(0.114)	(0.145)	(0.148)	(0.187)
Ln(Mgmt Team Size)	0.111	0.263**	0.098	0.209*
	(0.107)	(0.118)	(0.087)	(0.104)
Observations	743	577	743	577
Adjusted R-squared	0.154	0.186	0.124	0.137
Industry-by-Year-by-State FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 13: Placebo Test: The Effect of Top Management Changes on Corporate Innovation Generated Prior to Top Management Changes

This table reports the OLS regression results of corporate innovation generated over the past two or three years on top management changes. $Patents^{(-2)}$ is the natural log of one plus the number of patents filed in the past two years prior to management change; $Patents^{(-3)}$ is the natural log of one plus the number of patents filed in the past three years prior to management change; $Cites^{(-2)}$ is the natural log of one plus the adjusted number of citations received by patents filed in the past two years prior to management change; $Cites^{(-3)}$ is the natural log of one plus the adjusted number of citations received by patents filed in the past three years prior to management change. *Mgmt Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, industry fixed effects, financing year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	$\text{Patents}^{(-2)}$	$\text{Patents}^{(-3)}$	$\text{Cites}^{(-2)}$	$\text{Cites}^{(-3)}$
Mgmt Change	0.029	0.059	0.025	0.055
	(0.046)	(0.057)	(0.038)	(0.042)
Ln(VC Investment)	0.116***	0.122***	0.122***	0.129***
	(0.022)	(0.022)	(0.022)	(0.021)
Ln(Syndicate Size)	0.086	0.087	0.075	0.075
	(0.054)	(0.061)	(0.051)	(0.058)
Ln(Mgmt Team Size)	0.052	0.055	0.040	0.035
	(0.058)	(0.065)	(0.066)	(0.076)
Observations	976	976	976	976
Adjusted R-squared	0.165	0.173	0.125	0.138
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

Table 14: Robustness Test: Controlling for Lead VC Firm Fixed Effects

This table reports the OLS regression results of corporate innovation on top management changes controlling for the lead VC firm fixed effects. *Patents*$^{(2)}$ is the natural log of one plus the number of patents filed over the next two years; *Patents*$^{(3)}$ is the natural log of one plus the number of patents filed over the next three years; *Cites*$^{(2)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next two years; *Cites*$^{(3)}$ is the natural log of one plus the adjusted number of citations received by patents filed over the next three years. *Mgmt Change* is a dummy variable equal to one for a firm-financing round if there was a change in the composition of the top management team and zero otherwise. *Ln(VC Investment)* is the natural log of VC investment amount. *Ln(Syndicate Size)* is the natural log of one plus the number of investing VCs. *Ln(Mgmt Team Size)* is the natural log of one plus the total number of managers on the top management team. Intercept, lead VC firm fixed effects, industry fixed effects, financing year fixed effects, and startup development stage fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Patents$^{(2)}$	Patents$^{(3)}$	Cites$^{(2)}$	Cites$^{(3)}$
Mgmt Change	0.219***	0.267**	0.180**	0.222
	(0.064)	(0.111)	(0.075)	(0.155)
Ln(VC Investment)	0.119**	0.209**	0.113**	0.198*
	(0.056)	(0.087)	(0.053)	(0.103)
Ln(Syndicate Size)	0.118	0.072	0.079	-0.006
	(0.142)	(0.233)	(0.141)	(0.278)
Ln(Mgmt Team Size)	-0.068	0.008	-0.067	-0.011
	(0.187)	(0.194)	(0.155)	(0.161)
Observations	722	557	722	557
Adjusted R-squared	0.400	0.371	0.328	0.265
Lead VC Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes

2 Venture Capital Backing, Investor Attention, and Initial Public Offerings

2.1 Introduction

It is by now well established that venture capitalists add product market value to the private firms that they invest in, either by helping them to improve firm efficiency (Chemmanur, Krishnan, and Nandy (2011)) or through monitoring (see, e.g., Gompers (1995) or Lerner (1995)). However, practitioners also talk about venture capitalists helping to create value for the firm in the financial market at the time the firm goes public. The channels through which such value is created, however, are less well-understood. The objective of this paper is to explore a new channel through which VCs may create value in the IPO market for the private firms that they invest in over and above any value they have created for these firms in the product market. We propose a new channel through which VCs may create value at the time of IPO for a firm that they have invested in, namely, by attracting greater investor attention to the firm's IPO. Using proxies for investor attention, we first test whether VC-backed firm IPOs are indeed associated with greater investor attention relative to non-VC-backed firm IPOs. We then develop testable predictions regarding the implications of this ability of VC-backing to attract greater investor attention to a firm going public for various specific characteristics (e.g., firm valuation at IPO) of VC-backed versus non-VC-backed firm IPOs and empirically test these predictions.

An important hypothesis that has significant currency in the existing literature regarding financial market value-creation by VCs for their portfolio firms is the venture capital (VC) "certification hypothesis": see, e.g., Megginson and Weiss (1991). This hypothesis postulates that venture capitalists are able to "certify" the value of a firm backed by them to the financial market, thus reducing the information asymmetry faced by the firm in the IPO market. The argument here is that this reduces information asymmetry, and in turn, leads to a lower extent of underpricing for the IPOs of VC-backed firms relative to that for the IPOs of non-VC-backed firms. The certification hypothesis, however, has been called into question by the evidence from the 1990s and later, which shows that VC-backed IPOs were, in fact, more (not less) underpriced than non-VC-backed firm IPOs (see, e.g., Lee and Wahal (2004)). However, while the notion that VC-backing reduces underpricing has been contradicted by the empirical evidence, it is nevertheless possible that, given the empirical evidence that VCs select higher quality firms to invest in and add product market value to them (see, e.g., Chemmanur, Krishnan, and Nandy (2011)), investors may infer that a firm going public is of higher quality (intrinsic value) from the fact that it is VC-backed. The investor attention channel that we propose in this paper and the above "weak form" of the certification hypothesis are not mutually exclusive: we control for this certification effect in our empirical analysis.[28]

Precisely how may VC-backing affect the IPO characteristics of a firm when it goes public through the investor attention channel? To address this question, we start by assuming that for institutional investors to participate in a firm's IPO, they not only need to receive information about various aspects of that firm from an investment bank, but also to pay attention to or "recognize" this information. This last assumption is in the spirit of Merton's (1987) investor recognition or attention model, which assumes that an investor will incorporate a security into his portfolio only if he pays attention to (or acquires information about) that security. While Merton (1987) posits several possible sources of his "attention" or "recognition" cost, he views this cost mainly as arising from the cost of investors becoming aware of (or familiar with) a firm: in his setting, investors consider investing only in the

[28]We use the term "weak form" of the certification hypothesis to capture the notion that IPO market investors may infer that the firm is of higher quality from the fact that it is VC-backed (with implications for firm valuation and other IPO characteristics). This is in contrast to the stronger implications of the original certification hypothesis such as the reduction in information asymmetry facing a VC-backed firm or lower underpricing for VC-backed firms (compared to non-VC-backed firms), which can be thought of as arising from a "strong form" of the certification hypothesis. In order to establish that the investor attention channel of VC value creation in the financial market that we propose in this paper has effects on the IPO characteristics of VC-backed firms over and above any certification effects of VC-backing, we control for potential differences in intrinsic quality between VC-backed and non-VC-backed firms in a variety of ways (discussed in the main text).

stock of firms with which they have a certain level of familiarity. In a similar vein, we can think of institutional and other investors considering for investment only the stock of IPO firms that they have become familiar with by incurring a cost.[29]

We now make the additional assumption that the above attention cost for investors is lower for VC-backed IPOs compared to that for non-VC-backed IPOs. This may be because VCs are repeat players in the IPO market, so that institutional investors may have had repeated prior interactions with the VCs backing a given IPO firm. For example, some institutional investors may have previously invested in IPOs backed by one or more of the VCs backing the current IPO firm, and had a good experience from the point of view of their investment paying off a high return. Alternatively, they may have heard about other institutions having made such successful prior investments in IPOs backed by one or more of the VCs backing the current IPO firm. In the context of the Merton (1987) model, the above assumption implies that investors' cost of paying attention to VC-backed IPO firms will, on average, be lower compared to that for paying attention to non-VC-backed IPO firms. This, in turn, implies that more institutions are likely to pay attention to a particular IPO if that IPO is VC-backed relative to the situation where it is not VC-backed.[30]

The notion that VC-backed IPO firms may attract greater attention from institutional investors has important implications for the IPO pricing process, and in particular, for the book-building and road-show process in IPOs. The practitioner literature points to the two-way information flow occurring during the IPO road-show and book-building process between IPO underwriters and institutions: while underwriters collect information from institutions about their demand schedules for the IPO firm's shares during this process (information extraction), they also address institutions' questions and concerns about the future strategy and performance of the IPO firm (information dissemination). We can therefore think of two

[29]The Merton (1987) model has been extended by Van Nieuwerburgh and Veldkamp (2009), who assume that such attention/information acquisition has a cost. See also the theoretical IPO model of Liu, Lu, Sherman, and Zhang (2016) who also make such an assumption.

[30]By a similar argument, we expect institutions' attention cost to be lower for high-reputation VC-backed IPOs relative to that for low-reputation VC-backed IPOs. This, in turn, implies that institutions are more likely to pay attention to an IPO if it is high-reputation VC-backed rather than low-reputation VC-backed.

ways in which the greater investor attention that may be generated by the VC-backing of IPO firms may affect the characteristics of VC-backed versus non-VC-backed IPOs. First, such greater investor attention may affect the ability of a lead IPO underwriter to disseminate information about the IPO firm to institutional investors. Second, such greater investor attention may affect a lead IPO underwriter's ability to extract information from institutions about their demand for the IPO firm's equity.

We first discuss how VC-backing and the greater investor attention it draws to a firm's IPO affects information dissemination. An important strand in the theoretical literature on IPOs has argued that the role of an underwriter in an IPO is that of a producer of noisy information about the firm it takes public and a transmitter of that information to potential investors in its IPO: see, e.g., Booth and Smith (1986) or Chemmanur and Fulghieri (1994). However, unlike this literature, which has argued that a lead IPO underwriter transmits information to investors about the IPO using its reputation as a certification mechanism, we postulate here that the lead underwriter transmits noisy information about the IPO firm to potential IPO investors either directly, or through the other investment banks in the IPO syndicate.[31] As we discussed earlier, we have assumed that, for institutional investors to participate in a firm's IPO, they not only need to receive information about various aspects of that firm from the IPO underwriter, but also to pay attention to or "recognize" this information in the spirit of Merton's (1987) investor recognition model. This has an important implication for information dissemination. The implication is that, since, on average, a greater number of institutions will pay attention to an IPO if it is VC-backed, the dissemination of information about the IPO firm from the underwriter to institutions will be more efficient if the IPO is VC-backed. We will refer to this hypothesis as the "information dissemination through investor attention" hypothesis.

[31] Unlike their role in the certification literature, the role of lead IPO underwriters that we postulate here is essentially that of "marketing" IPOs to institutional investors making use of their investment banking syndicate and the ongoing relationships individual investment banks in the IPO syndicate may have with various institutional investors. See also a related paper by Gao and Ritter (2010), who analyze the effects of marketing efforts by underwriters in seasoned equity offerings.

We now turn to the effect of VC-backing on information extraction. The theoretical book-building literature that originated with Benveniste and Spindt (1989) has modeled an IPO underwriter as concerned with extracting truthful information from institutional investors who have private information about their own valuation of the IPO firm (and therefore their demand schedule for the firm's shares), and using the IPO share allocation process to design an incentive compatible mechanism to extract this information. In the above setting, we again introduce our assumption that institutions' cost of paying attention to an IPO is lower for VC-backed than for non-VC-backed firm IPOs, in which case institutional investors are more likely to pay attention to the IPO of a VC-backed firm rather than that of a non-VC-backed firm. Since a lead IPO underwriter has to first attract the attention of institutional investors to the firm whose IPO they are underwriting before they can extract information from them about their valuation of the firm's equity, this also implies that a lead IPO underwriter will be able to extract information from institutions more efficiently in the case of VC-backed IPOs relative to the case of non-VC-backed IPOs. We will refer to this hypothesis as the "information extraction through investor attention" hypothesis.[32]

In summary, we have argued above that an important effect of the VC-backing of IPOs is to induce a larger number of institutions to pay attention to IPO firms, thus making it easier for the lead underwriter to disseminate information about the firm to institutions and to extract information from them about their demand for the IPO firm's equity. As we discuss in detail in Section 2.3, this has implications for various IPO characteristics such as the absolute value of IPO offer price revisions; IPO and immediate secondary market valuations of the firm; IPO initial returns; and participation by institutional investors and financial analysts in IPOs or its immediate secondary market (the former by holding IPO

[32] Some of our discussion above of the effect of VC-backing on information dissemination and information extraction by IPO underwriters is parallel to the arguments made by Bajo, Chemmanur, Simonyan, and Tehranian (2016). Similar to our paper, they also focus on the ability of a lead underwriter to disseminate information to institutions and to extract information from them. Unlike our paper, however, the focus of that paper is on the effect of the centrality of lead IPO underwriters in their investment banking networks on their ability to efficiently disseminate information about IPO firms they take public to institutional investors and to extract information from them.

firms' equity and the latter by providing analyst coverage). We test these implications in our empirical analysis.

Before empirically analyzing the relation between VC-backing, investor attention, and various specific IPO characteristics, we first analyze whether VC-backed IPOs are indeed able to garner greater investor attention than non-VC-backed IPOs. In conducting this analysis, we make use of a proxy for investor attention developed by Liu, Sherman, and Zhang (2014), namely, pre-IPO media coverage received by the firm going public. Liu, Sherman, and Zhang (2014) argue that, since media sources compete to attract readers and advertising revenues, editors expect their reporters to cover those firms which have already received investor attention or are expected to receive such attention in the future. Consequently, the pre-IPO media coverage of firms going public serves as a good proxy for the degree of attention investors pay to such firms. We therefore make use of this proxy to test the notion that VC-backed IPOs are associated with greater investor attention.

We then move on to test the relation between VC-backing, investor attention, and various specific IPO characteristics. One difficulty with conducting such an analysis is that differences in various IPO characteristics between VC-backed and non-VC-backed firms may be driven by considerations other than differences in investor attention. For example, VC-backed and non-VC-backed firms may differ in terms of their intrinsic value (quality) pre-IPO. Such differences in intrinsic value may arise, for example, from VCs investing in higher quality firms to begin with (screening) or by VCs adding greater product market value to these firms pre-IPO (value addition or monitoring). Consequently, in our empirical analysis, we explicitly allow for the fact that differences in the IPO characteristics of VC-backed and non-VC-backed firms may be due to differences in their intrinsic quality (and the resulting valuation differences as inferred by investors: i.e., the certification effect) as well as their differences in investor attention (as proxied by media coverage) across the two kinds of IPOs. As we discuss below, we accomplish this in three different ways.

First, in our OLS analysis, we choose not to rely purely on comparisons of IPO characteristics between VC-backed versus non-VC-backed firms to test our hypotheses. Instead, we use interaction tests to split up the effect of VC-backing on various IPO characteristics (e.g., IPO valuation) into three components. The first component we identify is the direct effect of VC-backing, as captured by the coefficient of a VC-backing dummy, on IPO valuation. This component can be interpreted as coming partly from the higher intrinsic value of VC-backed firms (as inferred by the financial market).[33] The second component, whose effect is captured by the coefficient of our high (above median) investor attention dummy, can be interpreted as a "pure" investor attention effect: i.e., the direct effect of receiving higher investor attention on the IPO valuation of any firm (though, under our theory, we expect VC-backed firms to be more likely to receive higher investor attention than non-VC backed firms). The third component, whose effect is captured by the coefficient of the interaction term between VC-backing and the high investor attention dummy, can be interpreted as the incremental effect of higher investor attention on the valuation of VC-backed firms relative to that of non-VC-backed firms. Thus, we use our interaction tests to analyze whether there is an incremental effect of higher investor attention on various IPO characteristics of VC-backed firms even after controlling for the effect of possible differences in quality (intrinsic value) between VC- and non-VC-backed firms going public.

Second, we conduct a dynamic analysis of the difference in valuation between VC- and non-VC-backed firms, analyzing how firm valuation changes over the period of one, two, and three years after IPO for the two types of firms. Since we expect investor attention to dissipate (fade) to some extent after the IPO over time, we expect the differences in market valuation between VC and non-VC-backed firms (generated by the higher investor attention received by VC-backed firms) to become correspondingly smaller as time passes after the IPO. Further, if we assume that investor attention will decline to a greater extent (with

[33]Thus, a positive and significant coefficient of the VC-backing dummy in the regression of IPO valuation would indicate that VC-backed firms are valued higher on average than non-VC-backed firms at IPO: this could be partially due to VC-backed firms having higher intrinsic value than non-VC-backed firms, and partially due to VC-backed firms receiving greater investor attention than non-VC-backed firms. A similar interpretation of the VC-backing dummy holds in our regressions of other IPO characteristics as well.

the passage of time) for firms that received a higher level of such attention at the time of IPO (and assuming that the effect of investor attention is stronger on the valuation of VC-backed than that of non-VC-backed firms), we expect to find in our interaction test that the valuation of VC-backed firms that received higher (above median) investor attention at IPO declines to a greater extent post-IPO with the passage of time.[34]

Third, we control for the fact that VC-backing and investor attention (as well as favorable IPO characteristics) may be endogenous. In other words, it is possible that firms with certain intrinsic characteristics are more likely to receive VC backing as well as to receive greater investor attention, so that the greater investor attention and favorable IPO characteristics that we document for VC-backed firms may be due to these underlying intrinsic firm characteristics rather than due to VC-backing itself. We control for this endogeneity by instrumenting for VC-backing. Similar to the methodology of Samila and Sorenson (2011), the instrument we use for VC-backing is the product of the number of limited partners (who invest in VC funds) in the state where the IPO firm is headquartered and the average investment returns of college endowment funds for the ten years preceding the firm's IPO. Our instrument is motivated by the following three well-documented facts: First, the LPs of VC funds generally adopt an investing strategy that has a fixed optimal allocation ratio to distribute their investment over different asset classes, which includes equity, fixed income, and alternative assets (such as venture capital, private equity, and hedge funds). When university endowments earn higher returns, they are likely to shift more of their assets into venture capital to maintain the above optimal ratio. Second, these LPs exhibit a "home bias" when investing in venture capital, i.e., they are likely to invest in VC funds headquartered close to them. Third, VC funds also have a "home bias": i.e., they have a strong tendency to invest in entrepreneurial (private) firms close to them so that it is easier for them to monitor

[34]Using similar arguments, and under similar assumptions about the effect of investor attention fading over time (and assuming that the effect of investor attention is stronger on valuation of high-reputation VC-backed firms than that of low-reputation VC-backed firms), we expect the valuation of high-reputation VC-backed firms receiving higher (above median) investor attention to decline to a greater extent as time passes post-IPO.

and advise these firms (see, e.g., Tian (2011)). The above three facts collectively imply that higher endowment returns earned by LPs likely lead to more venture capital investments in firms in the same state as the LPs in the next few years, so that we expect our instrument to be positively related to the probability of VC-backing of a sample firm. We confirm that this is indeed the case empirically in the first stage of our IV analysis. The exclusion restriction for this instrument for VC-backing is also likely to be satisfied, since this instrument is likely to be unrelated to the underlying firm characteristics of the IPO firms in our sample.

The results of our analysis of the relation between VC-backing and investor attention can be summarized as follows. First, we find from our baseline regression analysis that VC-backed IPOs are associated with a greater amount of investor attention as proxied by pre-IPO media coverage. Second, high-reputation VC-backed IPOs receive greater investor attention than low-reputation VC-backed IPOs. Third, the second-stage regressions of our IV analysis with investor attention as the dependent variable show that VC-backed IPOs are associated with a greater amount of investor attention (as proxied by pre-IPO media coverage), and that this relation is causal.

We now discuss the results of our analysis of the relation between VC-backing, investor attention, and IPO characteristics. First, VC-backed IPOs are associated with larger absolute values of IPO offer price revisions. Further, our interaction tests reveal that, even after controlling for the direct effect of VC-backing, there is an incremental positive effect of higher (above median) investor attention received by VC-backed firms on the absolute value of IPO offer price revisions. Second, VC-backed IPOs are associated with greater IPO and secondary market valuations, and greater IPO initial returns. Further, our interaction tests reveal that, even after controlling for the direct effect of VC-backing, there is an incremental positive effect of higher (above median) investor attention received by VC-backed firms on IPO and secondary market valuations as well as on IPO initial returns.

The above results show two things. First, VC-backed firms have more favorable IPO characteristics, namely IPO and secondary market valuations and IPO initial returns, than non-VC-backed firms. Second, the fact that the coefficient of the interaction terms between higher investor attention and VC-backing is positive and significant in each of our OLS regression analyses of the above three IPO variables is consistent with the notion that the productivity of investor attention (in generating IPO and secondary market valuations and IPO initial returns) is greater for VC-backed than for non-VC-backed firm IPOs. This indicates that, even if part of the higher valuations (and higher IPO initial returns) of VC-backed over non-VC-backed IPO firms is due to differences in intrinsic firm quality, investor attention plays a significant role in generating higher values of these variables in VC-backed over non-VC-backed firm IPOs.

The results of our analysis of comparing the IPO characteristics of high- versus low-reputation VC-backed firms are broadly consistent with the above results. First, while we find that the coefficient of the VC-reputation dummy is not significantly different across high- versus low-reputation VC-backed IPOs in our regressions of IPO and secondary market valuations, it is significantly different in our initial return regression. Second, in our interaction tests comparing the IPO and secondary market valuations as well as the initial returns of high- versus low-reputation VC-backed IPOs, we find that high-reputation VC-backed firm IPOs receiving higher (above median) investor attention have higher IPO and secondary market valuations as well as IPO initial returns, compared to low-reputation VC-backed IPOs receiving higher (above median) investor attention, even after controlling for the direct effect of high- and low-reputation VC-backing. The fact that the coefficient of the interaction term between high-reputation VC-backing and higher investor attention is significantly greater than that of the interaction term between low-reputation VC-backing and higher investor attention in our analysis of the above IPO variables suggests that the productivity of investor attention in generating higher values of these IPO variables is greater for high-reputation VC-backed IPO firms.

The results of our analysis of the relation between VC-backing and participation by important financial market players in a firm's IPOs are also broadly supportive of the investor attention channel. First, VC-backed IPOs have a greater number of institutional investors holding the firms' equity and have greater analyst coverage post-IPO. Further, our interaction tests reveal that, even after controlling for the direct effect of VC-backing, there is an incremental positive effect of higher (above median) investor attention received by VC-backed firms on institutional investor participation and analyst coverage.

The results of our analysis of the dynamics of IPO firm valuation over time are also supportive of the investor attention channel. We find that the secondary market valuation of VC-backed IPO firms fall to a greater extent from the first trading day post-IPO through the three years following the IPO date. Further, our interaction tests reveal that, even after controlling for the direct effect of VC-backing, VC-backed firms that received higher (above median) investor attention have a greater fall in valuation as time passes after IPO.[35] These two results, taken together, suggest that the higher market valuation of VC-backed firms that we document at IPO is at least partially due to the greater investor attention received at IPO by such firms, as evidenced by their valuation falling to a greater extent as investor attention dissipates with the passage of time after IPO.

We now discuss the results of our IV analysis of the relation between VC-backing and various IPO characteristics. As mentioned earlier, we use our IV analysis to control for the possible differences in intrinsic quality between VC-backed and non-VC-backed firm IPOs, using the instrument for VC-backing discussed earlier. Our second-stage regressions with various IPO characteristics as dependent variables show that the positive relations between VC-backing and various IPO characteristics (the absolute value of offer price revisions, IPO and secondary market valuations, IPO initial returns, participation by institutional investors, and financial analyst coverage) that we document in our OLS analysis are causal.

[35] Similarly, our interaction test comparing high- and low-reputation VC-backed IPOs reveal that, even after controlling for the direct effect of venture capital reputation, high-reputation VC-backed IPO firms receiving higher (above median) investor attention have a greater fall in valuation over the three years after IPO compared to low-reputation VC-backed IPO firms receiving similar levels of (above median) investor attention. This is consistent with our earlier results showing that the productivity of high-reputation VC-backing in generating immediate post-IPO secondary market firm valuations is higher than that of low-reputation VC-backing. Clearly, given the earlier result, one would expect the fall in valuation as investor attention fades over time to be greater for high-reputation VC-backed IPOs as well.

The rest of this paper is organized as follows. Section 2.2 discusses how our paper is related to the existing literature and describes its contribution relative to this literature. Section 2.3 discusses the underlying theory and develops testable hypotheses. Section 2.4 describes our data and variables. Section 2.5 presents our analysis of the relation between VC-backing and investor attention. Section 2.6 presents our analysis of the relation between VC-backing, investor attention, and various IPO characteristics. Section 2.7 concludes.

2.2 Relation to the Existing Literature and Contribution

Our paper is most closely related to two different strands in the IPO literature. The first strand is the literature on the effects of VC-backing on IPO characteristics and its implications for the intermediation role played by VCs in the financial market. As we discussed earlier, an important early paper in this literature is Megginson and Weiss (1991), who document that VC-backing is associated with lower IPO underpricing (initial returns), which they attribute to the ability of VCs to certify firm value to the financial market. Another early paper is Barry, Muscarella, Peavy, and Vetsuypens (1990), who also document lower IPO underpricing for VC-backed IPOs, though this paper attributes this lower extent of underpricing to the intensive monitoring services provided by VCs and find that VC equity ownership, the length of board service, and the number of VCs invested in the pre-IPO firm are negatively related to IPO underpricing.[36] However, Lee and Wahal (2004) document that, controlling for the endogeneity in the receipt of VC funding, IPOs of VC-backed firms were, in fact, more underpriced on average than those of non-VC-backed firms between 1980 and 2000.[37] They cite their evidence as providing partial support for the grandstanding hypothesis of Gompers (1996), whereby younger VCs take the firms they have invested in public at an earlier age even at the expense of incurring a greater extent of underpricing, since this enables such VCs to establish a reputation for successful exits, thereby enhancing

[36] See also Li and Masulis (2007), and Krishnan Ivanov, Masulis, and Singh (2011) for similar arguments based on VC certification.

[37] Megginson and Weiss (1991) analyze VC- and non-VC-backed IPOs between 1983 and 1987, while Barry, Muscarella, Peavy, and Vetsuypens (1990) analyze such IPOs between 1978 and 1987.

their future fund-raising abilities.[38]

An important recent paper that gives a new rationale for why some IPOs are more underpriced than others is Liu and Ritter (2011). They argue that, while the underwriting industry is in general competitive, a small number of underwriters have market power and are able to provide greater coverage by "star analysts." This, in turn, generates the prediction that issuers who are less focused on maximizing IPO proceeds and more desirous of coverage by star analysts will have IPOs characterized by greater underpricing. They also attribute the greater underpricing of VC-backed IPOs to the "analyst lust" of VCs. Unlike Liu and Ritter (2011), in our setting, VC-backed IPOs receive greater analyst coverage endogenously as a consequence of the greater investor attention garnered by VC-backed firm IPOs. Further, while our empirical results documenting a positive relation between VC-backing and underpricing (IPO initial returns) are consistent with that of Liu and Ritter (2011), underpricing is only one among the many IPO characteristics we study in our empirical analysis: the focus of our paper is on establishing the ability of VC-backing to generate greater investor attention as a channel for value creation by venture capitalists in IPOs.

In summary, while related to the above literature analyzing the effect of VC-backing on various IPO characteristics, this paper contributes uniquely to this literature by establishing a new channel through which VC-backing creates value at IPO for the entrepreneurial firms they that invest in. It is also worth pointing out that the investor attention channel of value creation by VCs in the financial market that we propose and analyze in this paper may coexist with other channels that have been proposed in the existing literature, such as VC certification of firms and intensive monitoring of firm management by VCs pre- and post-IPO. In fact, by controlling for the direct effect of VC-backing, we are able to account for

[38]A number of other papers document somewhat similar results. Bradley and Jordan (2002) show that, once they control for industry effects and underwriter quality, there is no significant difference in underpricing between VC- and non-VC-backed IPOs during the period 1990-1999. Brav and Gompers (2003) find that underpricing is more severe among VC-backed firms during the 1990s. Hamao, Packer, and Ritter (2000) do a similar comparison for Japanese VC-backed and non-VC-backed firm IPOs during the 1990s and find that underpricing is more severe for VC-backed firm IPOs. See also Chemmanur and Loutskina (2004), who note that IPO underpricing may not be the most appropriate measure to evaluate the role of VC-backing in IPOs.

the differences in intrinsic value between VC- and non-VC-backed firm IPOs (and therefore the VC certification and monitoring effects documented in the existing literature) even in our baseline analysis of various IPO characteristics.

The second strand in the IPO literature to which our paper is related is the broader theoretical and empirical literature on IPOs: see Ritter and Welch (2002) for a review.[39,40] Apart from the IPO papers discussed earlier, our paper is related to several other papers in this literature. In an important paper, Liu, Sherman, and Zhang (2014) show that pre-IPO media coverage is positively related to the long-term equity value, liquidity, analyst coverage, and institutional investor ownership of the equity of firms going public. Another related paper is by Bajo, Chemmanur, Simonyan, and Tehranian (2016) who show that lead underwriters located more centrally in the networks of investment banks induced by their prior underwriting activity are able to generate more favorable IPO characteristics for the firms they take public, by attracting greater investor attention, and thereby disseminating information more efficiently to institutions and by better extracting information from them.[41] While our result that the extent of investor attention received by a firm is positively related to its IPO characteristics such as IPO valuation and initial returns is consistent with those in the above two papers, ours is the first paper in the literature that analyzes the relation between VC-backing and investor attention. Ours is also the first paper in the literature to

[39] In particular, the broader empirical literature studying the information flows in IPOs (e.g., Hanley (1993)) and the more recent studies on the efficiency of the IPO process in general (e.g., Lowry and Schwert (2004)) are also related to our paper.

[40] Some examples of information-driven theoretical models of IPO underpricing are Chemmanur (1993); Allen and Faulhaber (1989); Sherman (1992); Welch (1989); and Welch (1992). To the extent that our study is related to information flows around a firm's IPO, it is also indirectly related to models of going public versus remaining private decision driven by the desire of firm insiders to avoid revealing private information (e.g., Bhattacharya and Ritter (1983)) or by considerations of minimizing duplication in information production by outsiders (e.g., Chemmanur and Fulghieri (1999)).

[41] Our paper is also distantly related to the literature relating media coverage, equity trading volume, and stock returns in an asset pricing context. Fang and Peress (2009) show that stocks with no media coverage earn higher returns than stocks with high media coverage, even after controlling for well-known risk factors. Bodnaruk and Ostberg (2009) find supportive evidence of the Merton (1987) investor recognition effect using Swedish data. Tetlock (2007) analyzes daily content from a popular Wall Street Journal column and find that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and that high or low pessimism predicts high market trading volume. Engelberg and Parsons (2011) analyze the relation between media coverage and stock market trading volume and make use of differences in local media coverage to identify the causal effect of media coverage on investor trading.

propose investor attention as a channel through which VCs create value in the IPO market for the firms that they invest in, and the first to empirically analyze how VC-backing affects IPO characteristics through the investor attention channel.

Our paper is also distantly related to the literature on the selection of private firms to invest in by venture capitalists as well as that on value addition by VCs (in the product market) subsequent to their investment in these firms (but pre-IPO). Some papers have documented that venture capitalists may invest in higher quality private firms to begin with: see, e.g., Sørenson (2007), who makes use of an "assortive" matching model to show that more experienced VCs invest in better firms. A number of other papers have shown that VCs add value to the private firms in which they invest in a variety of ways: for example, by playing a role in the monitoring and management of these companies (Gorman and Sahlman (1989), Sahlman (1990), and Gompers and Lerner (1999)), by professionalizing firm management (Hellman and Puri (2002)), and improving firm efficiency (Chemmanur, Krishnan, and Nandy (2011)). Given this value addition, it is possible that, on average, VC-backed firms differ from non-VC-backed firms in a variety of ways including having a higher intrinsic value. However, our analysis goes through even if this is the case, since, in our empirical analysis, we explicitly take into account the fact that VC-backed firms may differ in intrinsic value (quality) from non-VC-backed firms. In contrast to the above literature, the focus of this paper is to show that, for a firm with a given intrinsic value at the time of IPO, VC-backing creates additional value in the IPO market by garnering enhanced investor attention to the firm's IPO, yielding higher IPO and secondary market valuations and other favorable IPO characteristics.

2.3 Theory and Hypothesis Development

In the introductory section of this paper, we introduced the notion that VC-backing may attract greater investor attention to an IPO firm, and discussed two ways in which this may affect the IPO characteristics of VC-backed versus non-VC-backed firms. First, the greater investor attention brought about by VC-backing may make information dissemination about the IPO firm by the IPO underwriter to institutional investors more effective. Second, such enhanced investor attention may allow the IPO underwriter to credibly extract information from institutional investors more efficiently about their valuation of the IPO firm. We refer to these two ways in which VC-backing may affect IPO characteristics as the "information dissemination through investor attention hypothesis" and the "information extraction through investor attention hypothesis," respectively.[42] In this section, we develop testable implications for the relationship between the VC-backing of firms going public and various characteristics of the IPOs of these firms based on these two broad hypotheses.

2.3.1 Relation between VC-Backing and Investor Attention

We argued earlier that VC-backed IPOs may receive greater investor attention and are thereby able to obtain more favorable IPO characteristics (such as higher IPO and immediate secondary market valuations, greater institutional investor participation, and financial analyst coverage). If indeed an important mechanism through which the IPOs of VC-backed firms obtain more favorable IPO characteristics is by attracting a larger number of institutions to pay attention to these firms, then we would expect proxies for investor attention to be greater for VC-backed relative to non-VC-backed IPOs. We follow Liu, Sherman, and Zhang (2014) and use the pre-IPO media coverage received by a firm going public as a proxy for investor attention paid to that firm (see Section 2.4.1 for a detailed discussion of our two proxies and why they are appropriate proxies). Thus, we expect greater pre-IPO media coverage for the IPOs of VC-backed firms compared to those of non-VC-backed firms (**H1**).

[42] We would like to emphasize that the two roles of the lead IPO underwriter during IPO road-shows and the book-building process that we discussed in the introduction are not mutually exclusive, though, in some contexts, one or the other role may dominate. Indeed, the practitioner literature on IPOs points to the two-way information flow occurring during IPO road-shows and the book-building process between IPO underwriters and institutions: while, on the one hand, underwriters collect information about the demand schedule of institutional investors for the IPO firm's shares, they also address institutional investors' questions and concerns about the future strategy and performance of the firm going public, thus disseminating information about the IPO firm to them. It is therefore not our objective to empirically distinguish between the information dissemination and information extraction roles of the lead IPO underwriter during IPO road-shows and the book-building process.

Further, if indeed VC-backed IPOs receive greater investor attention relative to non-VC-backed IPOs, due to VCs being repeat players in the IPO market, we would expect this effect to be stronger in the case of high-reputation VCs than in the case of low-reputation VCs. This is because high-reputation VCs may have taken more higher intrinsic value firms public in the past and therefore may have had even more favorable prior interactions with institutional investors than low-reputation VCs (as well as having a better track record in terms of the post-IPO performance of firms they have taken public). This is the next hypothesis (**H2**) that we test here.

In the following subsections, we develop testable hypotheses regarding the effect of the higher investor attention that will be garnered by a VC-backed firm (as we postulated) on various IPO characteristics of such firms.

2.3.2 VC-Backing, Investor Attention, and the IPO Pricing Process: Initial Offer Price Range, the IPO Offer Price, and the Secondary Market Price

We now discuss the specific relation that we have in mind between the VC-backing of an IPO firm, the greater investor attention that VC-backing generates, and its effect on the IPO pricing process. In particular, we characterize the setting of the initial IPO offer price range by the lead IPO underwriter and the firm, offer price revision during the book-building process leading to the determination of the final IPO offer price, and the subsequent determination of the post-IPO share price in the immediate post-IPO secondary market. The timing of various events that we postulate (as depicted in Figure 1) is the following. First, the firm and its lead underwriter agree on the initial range of offer prices (sometimes referred to as the "preliminary offer price range" or "initial filing range") within which they expect to set the final offer price. Second, the lead underwriter attempts to attract the attention of various institutions to the firm whose IPO it is underwriting. We assume here, as discussed earlier, that institutions' cost of paying attention to an IPO firm is lower for VC-backed firms than for non-VC-backed firms. Third, the lead underwriter disseminates information about

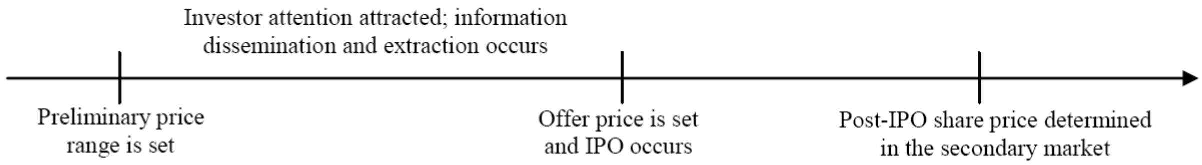

Figure 1: Timeline of the IPO Pricing Process

the characteristics of the IPO firm to the institutions whose attention it has been able to attract to the firm's IPO. Finally, the lead underwriter extracts information from the above institutions about their demand schedule for the IPO firm's equity.[43] The final offer price is set by the lead IPO underwriter as a result of the above information dissemination and extraction process; this may also affect the immediate post-IPO share price of the firm as well.

Consider first the determination of the initial IPO offer price range by the lead underwriter. To the best of our knowledge, there has been no formal theoretical model in the existing literature regarding the process by which an underwriter and issuer choose this initial offer price range; our objective here is not to develop such a model. Rather, the process we describe below is meant only to capture the trade-offs facing a lead underwriter when setting this initial offer price range. We make two important assumptions here about the process of setting the initial offer price range. First, while the lead underwriter is aware of its expected ability to attract investor attention to a particular IPO and the noisy information about the IPO firm that it wishes to convey to these investors, it will have residual uncertainty about the precise amount of attention it will be able to attract from institutions to the IPO and therefore about the amount of information it will be able to convey to these institutions about the firm going public.[44] This means that the lead underwriter will choose

[43]While, for concreteness, we have specified the timing of information extraction as occurring after information dissemination, our testable predictions remain qualitatively unchanged even if there is some overlap between the timing of information dissemination and information extraction by the lead underwriter.

[44]This uncertainty may arise for various reasons. For example, there may be other important (and unforeseen) events occurring at the time of a given IPO that may affect the stock market and the economy as a whole, which can affect the attention that institutions pay to the IPO: see, e.g., Liu, Sherman, and Zhang (2014) who discuss the possibility of other contemporaneous news events affecting the investor attention (and media coverage) achieved by a particular firm's IPO.

the initial IPO offer price range based on the expected value of the investor attention that it will be able to attract to the IPO and the expected value of the effect of its information dissemination on the firm's final IPO offer price, with the precise value of these variables being realized only subsequently (during the book-building process). Second, we assume that, while the lead underwriter is free to set the final offer price anywhere within the initial offer price range (and if necessary above or below this range), it is costly for the lead underwriter to set the offer price significantly above or below the midpoint of this range: for simplicity, we assume that this cost is increasing in the distance of the final offer price from the midpoint of the initial IPO offer price range.[45]

The above two assumptions imply that the cost-benefit trade-off driving a lead underwriter's choice of the initial IPO offer price range is as follows. If a lead underwriter sets the midpoint of the initial IPO offer price range significantly below the expected final IPO offer price, it will have to incur the cost of revising the price upward in the event the demand from institutions for the IPO firm's shares is strong (in order to maximize IPO proceeds). If, however, the lead underwriter sets the midpoint of the initial IPO offer price range significantly above the expected final IPO offer price, it will have to incur the cost of revising the price downward in the event the demand from institutions for the IPO firm's shares is weak (to ensure that all the shares offered in the IPO are sold out, and the firm is able to raise the amount of financing it needs). The above trade-off implies that a lead underwriter will set the midpoint of the initial IPO offer price range equal to its expectation of the final IPO offer price.[46]

[45]Such a cost may arise, for example, from underwriters losing reputation with institutions: the latter may have devoted considerable resources to evaluating the IPO firm based on the initial offer price range set by the underwriter, and some of these resources may be wasted if the final offer price is set significantly away from the initial offer price. See, e.g., Bajo, Chemmanur, Simonyan, and Tehranian (2016) for a more detailed discussion.

[46]The empirical and anecdotal evidence is somewhat consistent with the process of setting the initial IPO offer price (filing) range that we postulate here. While there is no consensus in the literature on this point, some of the empirical studies on IPOs have used the midpoint of the initial IPO offer price range as an unbiased predictor of the ultimate IPO offer price: see, e.g., Hanley (1993), Loughran and Ritter (2002), and Bradley and Jordan (2002). However, Lowry and Schwert (2004) document that the midpoint of the initial IPO offer price range is not always an unbiased predictor of the final IPO offer price: in their sample, the final IPO offer price is set about 1.4% below the midpoint of the initial IPO offer price range, on average.

After the initial offer price range is chosen and the information about the IPO firm is disseminated to the institutions who pay attention to it, the lead underwriter extracts information from these institutions about their demand for the IPO firm's shares. The offer price will be revised upward or downward from the midpoint of the initial offer price range depending on the above information extracted by the lead underwriter from institutions. Since the lead IPO underwriter of a VC-backed firm will be able to attract attention from a larger number of institutions for the firm it is taking public (relative to the situation in the case of a non-VC-backed firm), it will be able to more efficiently extract information useful for valuing a VC-backed IPO firm's shares from institutions. If this is the case, we would expect a positive relationship between VC-backing and the absolute value of the IPO offer price revision under the information extraction hypothesis (**H3A**), since a greater amount of information will be extracted from institutions in this case.[47] Further, assuming that the effect of investor attention is stronger in the case of VC-backed IPOs than in the case of non-VC-backed IPOs, the information extraction hypothesis implies that, VC-backed firms receiving higher (above median) investor attention will be associated with a larger absolute value of IPO offer price revision, even after controlling for the direct effect of VC-backing.[48]

A lead IPO underwriter of a VC-backed firm may also be in a position to disseminate information more efficiently about the firm to institutions, given institutions' lower cost of paying attention to VC-backed firms. Since the lead underwriter knows the expected value of the effect of its information dissemination on the final IPO offer price, the expected effect of this more efficient information dissemination will already be incorporated into the mid-point of the initial IPO filing range (recall that, as we discussed above, the underwriter sets

[47]The above implication assumes that the information that a lead underwriter uses in setting the initial IPO offer price range is obtained from the process of writing the initial IPO prospectus, and the process of gathering more information from institutional investors begins only after that (during the book-building process).

[48]For all IPO characteristics, we empirically analyze whether the incremental effect of higher investor attention received by VC-backed compared to non-VC-backed firms (after controlling for the direct effect of VC-backing) making use of interaction tests. Thus, we expect the coefficient of the interaction between VC-backing and higher investor attention to be positive or negative according as this incremental effect of investor attention is greater or smaller in VC-backed firms.

the midpoint of the initial IPO offer price range equal to its expectation of the final IPO offer price). However, since lead underwriters will be able to disseminate information more efficiently (and accurately) to institutions in the case of VC-backed firms, the realization of information dissemination during the book-building process will be closer to the midpoint of the initial IPO offer price range for VC-backed firm IPOs compared to non-VC-backed firm IPOs. This implies that we would expect a negative relationship between VC-backing and the absolute value of the IPO offer price revision under the information dissemination hypothesis (**H3B**). Further, assuming that the effect of investor attention is stronger in the case of VC-backed IPOs than in the case of non-VC-backed IPOs, the information dissemination hypothesis implies that, VC-backed firms receiving higher (above median) investor attention will be associated with a smaller absolute value of IPO offer price revision, even after controlling for the direct effect of VC-backing.

We now turn to the relationship between VC-backing and immediate post-IPO secondary market valuation (we discuss the various valuation measures we use in Section 2.4.3). As we discussed earlier, underwriters may be able to induce more institutions to pay attention to the information they are disseminating about VC-backed IPO firms that they take public, since institutions will have a smaller cost of paying attention to the IPOs of VC-backed firms compared to the situation where they take a non-VC-backed firm public. Assuming that a given fraction of institutions paying attention to an IPO firm choose to invest in its equity, this means that the market clearing price for the shares of a VC-backed IPO firm will be greater than the market clearing price of a non-VC-backed firm (of the same intrinsic value). Further, since the expected secondary market IPO firm value will equal this the market-clearing price, this implies that VC-backed IPO firms will be associated with higher immediate post-IPO secondary market valuations than similar non-VC-backed firms (**H4**).[49]

[49] The immediate secondary market as well as IPO valuations of VC-backed firms may be greater compared to those of non-VC-backed firms driven by considerations other than differences in investor attention. For example, VC-backed and non-VC-backed firms may differ in terms of their intrinsic value pre-IPO. Such differences in intrinsic value may arise, for example, from VCs investing to higher quality firms to begin with (screening) or by VCs creating greater product market value for these firms pre-IPO (monitoring). Given this possibility, we chose not to focus on simple comparisons between VC-backed versus non-VC-backed firms

Further, assuming that the effect of investor attention is stronger in the case of VC-backed IPOs than in the case of non-VC-backed IPOs, we would expect VC-backed firms receiving higher (above median) investor attention to be associated with higher immediate post-IPO secondary market valuations even after controlling for the direct effect of VC-backing.[50]

Next, we discuss the relationship between VC-backing and firm valuation at the IPO offer price. This relationship depends on the process of setting the offer price in IPOs. While there is no consensus in the theoretical and empirical 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, the lead underwriter may convey information about the IPO firm to institutions (this, in turn, may affect their valuation of the firm). The lead underwriter may then extract information from institutional investors about their valuation of the IPO firm. Toward the end of the book-building and road-show process, once the lead underwriter establishes 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), the underwriter may apply a "discount" to this price, thus establishing the actual IPO offer price (typically on the evening before the IPO). The theoretical literature has made various arguments regarding the main driving force behind this discount. A prominent reason for this discount that has been advanced by Benveniste and Spindt (1989) is that this discount ensures that institutional investors have the incentive to reveal their true demand for the firm's equity (i.e., it ensures that their incentive compatibility or truth-telling conditions will hold). Since VC-backing may induce a larger number of institutions to pay attention to the IPO of a given firm (so that a larger number of institutions may participate in the book-building process of that IPO), the Benveniste and Spindt (1989) argument predicts that only a smaller discount to the

to test our hypotheses. Rather, we also focus on the interaction tests between VC-backing and proxies for investor attention in our empirical analyses of IPO and secondary market valuations.

[50] A higher after-market price may also arise from considerations of information extraction, since more complete knowledge and more accurate valuation of an IPO firm's shares means less risk for investors, and hence a smaller risk premium (assuming that investors are risk-averse on average).

market-clearing price will be required for the IPOs of VC-backed firms to ensure truth-telling by institutions. This, in turn, implies that the relationship between VC-backing and firm valuation at the IPO offer price will be unambiguously positive (**H5A**). Further, assuming that the effect of investor attention is stronger in the case of VC-backed IPOs than in the case of non-VC-backed IPOs, we would expect VC-backed firms receiving higher (above median) investor attention to be associated with higher valuations at the offer price even after controlling for the direct effect of VC-backing.

On the other hand, if the discount from the expected after-market price is used to compensate institutional investors for their opportunity cost of paying attention to a particular IPO (as argued by Liu, Lu, Sherman, and Zhang (2016)) in addition to ensuring truthful revelation of information by these investors (as in Benveniste and Spindt (1989)), then lead underwriter may apply a higher discount to the expected first day secondary market closing price for VC-backed IPOs.[51] If this is indeed the case, the predicted relationship between VC-backing and the IPO offer price becomes ambiguous (**H5B**). This is because the greater after-market price associated with the IPO of a VC-backed firm (that we postulated earlier) may be overcome by a larger discount, so that the relationship between VC-backing and firm valuation at the IPO offer price may even turn negative.

Finally, we turn to the relationship between VC-backing and IPO initial returns (underpricing). Given our discussion above regarding the potentially ambiguous relationship between VC-backing and the discount applied by the underwriter to the market-clearing (expected after-market) price to arrive at the IPO offer price, we are agnostic about the relationship between VC-backing and IPO initial returns.[52] Following our discussion above, if

[51] To better understand why lead underwriters may apply a larger discount to the expected secondary market price to arrive at the IPO offer price, note, as we argued earlier, that such IPOs will attract greater investor attention. In equilibrium, such underwriters need to compensate these institutional investors for their opportunity cost of paying attention to these IPOs (as argued by Liu, Lu, Sherman, and Zhang (2016)). In the above setting, if institutions' *aggregate* cost of paying attention to VC-backed IPOs is greater (taking into account the smaller cost per investor for paying attention to a VC-backed IPO but the greater attention paid to these IPOs by institutions collectively), then the "money left on the table" (the dollar amount of the IPO discount multiplied by the number of shares sold) has to be greater for VC-backed IPO firms.

[52] Clearly, the greater the discount applied by the lead underwriter to the first day expected secondary market closing price of an IPO (assumed here to be the same as the market-clearing price) to arrive at the

the above discount is driven primarily by the need to extract truthful information from institutions (as argued by Benveniste and Spindt (1989)), then we would expect this relationship between VC-backing and the discount to be negative (**H6A**), since lead underwriters will apply a smaller discount to the expected after-market price to arrive at the IPO offer price in the case of VC-backed firms. If, however, this relationship is driven also by considerations of compensating institutions for their opportunity cost of paying attention to the IPO firm (as argued by Liu, Lu, Sherman, and Zhang (2016)), then we would expect the relationship between VC-backing and IPO initial returns to be positive (**H6B**). We are agnostic of about the sign of coefficient on the interaction between VC-backing and investor attention, since it may be positive or negative depending on whether it is **H6A** or **H6B** that holds.

2.3.3 The Effect of VC Reputation on the Relation between Investor Attention and IPO Characteristics

Analogous to our analysis of the relation between VC-backing, investor attention, and IPO characteristics, we also conduct an analysis of the relation between VC reputation, investor attention, and three IPO variables: immediate secondary market valuation, IPO valuation, and IPO initial returns. As we argued earlier, we expect institutions' cost of paying attention to information disseminated by lead IPO underwriters about firms backed by higher reputation VCs to be lower than those backed by lower reputation VCs. Therefore, by arguments similar to that we have made above in the context of VC-backing (when developing our hypothesis **H4**), high-reputation VC-backed IPOs will be associated with higher immediate secondary market valuations compared to those backed by low-reputation VCs. Further, assuming that the effect of investor attention on secondary market valuation is stronger in the case of high-reputation VC-backed firm IPOs compared to that of low-reputation VC-backed firm IPOs, we would expect such IPOs receiving high (above median) investor attention to have higher secondary market valuations compared to low-reputation VC-backed IPOs re-

IPO offer price, the greater the initial return will be.

ceiving high (above median) investor attention, even after controlling for the direct effect of high- and low-reputation VC-backing.[53]

We also conduct an analysis comparing IPO valuations of high- and low-reputation VC-backed IPOs. By arguments similar to that we have made earlier (when developing hypotheses **H5A** and **H5B**), high-reputation VC-backed IPOs may have greater or lesser valuations compared to those of low-reputation VC-backed IPOs (depending on whether higher secondary market valuations for the former IPOs are overcome by the larger discounts applied by underwriters in setting the IPO offer price). Further, if considerations of information extraction dominate and assuming that the effect of investor attention is stronger in the case of high-reputation VC-backed firm IPOs compared to that of low-reputation VC-backed firm IPOs, we would expect that high-reputation VC-backed firm IPOs receiving higher (above median) investor attention will have higher valuations at the IPO offer price compared to low-reputation VC-backed IPOs receiving higher (above median) investor attention, even after controlling for the direct effect of high- and low-reputation VC-backing.

Finally, we conduct an analysis comparing the initial returns of high- and low-reputation VC-backed IPOs. By an argument similar to that we made in developing hypotheses **H6A** and **H6B**, we would expect high-reputation VC-backed IPOs to have a greater or smaller intial returns than that for low-reputation VC-backed IPOs, depending upon whether or not information extraction considerations dominate that of compensating institutions for paying greater investor attention to the former category of IPOs. Further, assuming that the effect of investor attention is stronger in the case of high-reputation VC-backed firm IPOs compared to that of low-reputation VC-backed firm IPOs, and depending on whether it is **H6A** or **H6B** that holds, we would expect high-reputation VC-backed firm IPOs receiving higher

[53]There is significant empirical evidence that high-reputation venture capitalists take higher quality firms public compared to low-reputation venture capitalists. This means that the nature of information disseminated to institutional investors by lead underwriters of high-reputation VC-backed IPO firms about the firms going public (or that of the information extracted by lead IPO underwriters from institutions about these firms) may be fundamentally different from the information disseminated (or extracted) by lead underwriters of low-reputation VC-backed IPO firms. This in turn, may lead to differential effects of investor attention on the immediate post-IPO secondary market as well as IPO valuations of firms backed by high- and low-reputation VCs.

(above median) investor attention to have lower or higher IPO initial returns compared to low-reputation VC-backed IPOs receiving higher (above median) investor attention, even after controlling for the direct effect of high- and low-reputation VC-backing.

2.3.4 VC-Backing, Investor Attention, and the Participation of Financial Market Players in IPOs

We have argued so far that the lead IPO underwriters may be able to induce a larger number of institutions to pay attention to the IPOs of VC-backed firms. This implies that participation by institutional investors (i.e., institutional investor investments in the equity of the IPO firm) will be greater for such IPOs (**H7**). Further, the grater amount of investor attention (as proxied by pre-IPO media coverage) received by a VC-backed firm IPO, the greater the institutional investor investment in the equity of that IPO firm even after controlling for the direct effect of VC-backing.

Given that financial analysts are either engaged in conveying information about the IPO firm to institutions (sell-side analysts affiliated with investment banks in the IPO underwriting syndicate) or in acquiring information on behalf of institutions (buy-side analysts affiliated with various institutions) we would also expect greater analyst coverage to be received by VC-backed firm IPOs (**H8**). Further, the greater the amount of investor attention (as proxied by pre-IPO media coverage) received by a VC-backed firm IPO, the greater analyst coverage received by that IPO firm even after controlling for the direct effect of VC-backing.

2.3.5 The Dynamics of the Secondary Market Valuation of IPO Firm Equity

We argued in Section 2.3.2 that VC-backed IPO firms may receive greater valuations in the immediate post-IPO secondary market due to, among other reasons, the greater amount of investor attention they receive around their IPO. We now explore the dynamic changes in the valuations of VC-backed and non-VC-backed IPO firms over time. To develop testable hypotheses for our dynamic analysis of VC valuation, we make two assumptions. First, we assume that investor attention fades significantly as time passes after the IPO. Second, we assume that investor attention will decline to the greatest extent (with the passage of time) for firms that received the highest level of such attention at the time of IPO. Under these two assumptions, we get two testable implications. First, the valuation of VC-backed IPO firms will fall to a greater extent than that of non-VC-backed firms, assuming that a significant portion of their immediate secondary market value is due to the greater investor attention they received around the IPO (**H9**).[54] Second, we expect the valuation of VC-backed firms receiving the greatest investor attention at IPO to decline to the greatest extent post-IPO (corresponding to the greater decline in investor attention received by these firms over time) (**H10**). By a similar argument, in our analysis comparing the dynamics the secondary market valuations of high- and low-VC-backed IPOs, we expect that the valuation of high-reputation VC-backed firms receiving high investor (above median) attention at the IPO to decline to a greater extent than that of low-reputation VC-backed firms receiving high investor attention.

2.4 Data and Sample Selection

The data used in this study came from multiple sources. We obtain the list of initial public offerings in the US from 1980 to 2009 from the SDC/Platinum Global New Issues database. In line with the IPO literature, we exclude equity offerings of financial institutions (SIC codes between 6000 and 6999) and regulated utilities (SIC codes between 4900 and 4999), unit offerings, closed-end funds, real estate investment trusts (REITs), American Depositary Receipts (ADRs), rights issues, spin-offs, equity carve-outs, leverage buyouts, tracking stocks, issues with offer price less than $5, issues with incomplete information on offer price and the number of shares filed in an IPO, and duplicates. The IPO firm should issue common shares (with share code headers of 10 and 11 in CRSP). We further require that the issuing

[54] As we discussed earlier, VC-backed and non-VC-backed IPO firms may also differ in intrinsic value, driven by product market considerations associated with VC-backing. The implications we are deriving in this subsection assumes that the drivers of higher valuation in VC-backed firms other than the greater investor attention received by a VC-backed firm IPO, remain constant as time passes after IPO.

firm must be present on the Compustat annual industrial database for the fiscal year prior to the offering and at least for one year after the offering, as well as on the CRSP database within sixty days of the issue date. Though the SDC/Platinum Global New Issues database provides the venture flag which can be used to identify venture-backed IPOs, we cross check this by merging our list of IPOs with the VentureXpert database. We drop IPO firms that are classified as VC-backed in the SDC/Platinum Global New Issues database but as non-VC-backed in VentureXpert or vice versa from our sample.

We end up with 4105 IPOs that satisfy these criteria, out of which 1876 are VC-backed IPOs and 2229 are non-VC-backed IPOs. The median offer price of the IPO firms in our sample is $12.00, median sales are $43.0 million, median EBITDA is $4.65 million, and median net income is $1.58 million. These characteristics of our IPO sample are comparable to those in other studies (see, e.g., Loughran and Ritter (2004)). Information on IPO underwriters as well as various IPO characteristics is taken from the SDC/Platinum Global New Issues database. The data for constructing the VC reputation measure came from VentureXpert. Information on institutional investors was obtained from Thomson Reuters Institutional Holdings (13F) Database. Analyst coverage data came from Institutional Brokers Estimate System (I/B/E/S). Accounting data came from Compustat and stock price data came from CRSP. Table 1 provides the summary statistics of our sample.

2.4.1 Proxies for Investor Attention

In order to assess the degree of attention that investors pay to IPO firms, we make use of two measures of pre-IPO media coverage of firms going public following Liu, Sherman, and Zhang (2014), who use media coverage as a proxy for investor attention. Liu, Sherman, and Zhang (2014) argue that media sources compete to attract readers and advertising revenues and, consequently, editors expect their reporters to cover the firms which have already received investor attention or are expected to receive such attention in the future. Even though media coverage does not contain any new “hard” information about the IPO firm (such "hard" information must be disclosed in the IPO prospectus), the fact that the firm receives coverage indicates that reporters and/or their sources expect the firm to attract investor attention. According to Liu, Sherman, and Zhang (2014), when choosing a firm to cover, reporters use not only their own judgment but also talk to Wall Street professionals, so that media coverage of IPO firms will be more than mere noise. While media coverage may include some firms due to short-term demand from retail investors who are driven by sentiment, it will also include firms that sophisticated investors care about. Given the above, the pre-IPO media coverage of firms going public is a good proxy for the degree of attention investors pay to such firms.

We construct two measures of pre-IPO media coverage of firms going public by searching all U.S. English language media sources in Factiva for news articles as well as the headlines of articles covering IPO firms in our sample. Our first measure is *Headlines*, which is the number of article headlines that have mentioned the IPO firm in the two months prior to the IPO date: this measure has been used by Bajo, Chemmanur, Simonyan, and Tehranian (2016). Our second measure is *Articles*, which is the number of articles that have mentioned the IPO firm in the two months prior to the IPO date (used by both Liu, Sherman, and Zhang (2014) and Bajo, Chemmanur, Simonyan, and Tehranian (2016)). As shown in Table 1, a typical firm in our sample is covered by 2 headlines and 10 articles in the two months prior to its IPO. Since the distribution of *Headlines* and *Articles* are right skewed, we use the natural log of one plus the actual number of headlines and that of articles (*Ln(Headlines)* and *Ln(Articles)*) in our regressions. We also construct two dummy variables, *High Headlines* and *High Articles*, to indicate that the number of headlines and that of articles covering the IPO firm are above the sample median, respectively.

2.4.2 Measures for VC Reputation

In this section, we describe how we construct our reputation measure for the lead VC investors that invested in VC-backed IPO firms. To determine lead VC investors, we merge our list of

VC-backed IPOs with the VC investment level data from VentureXpert. Following Nahata (2008), we define the lead VC as the VC firm that participated in the first round and made the largest total investment in the company across all rounds. If the identities of investors in the first round are not available, we use the same logic to identify the lead VC firm based on investors' information in the second round. We require the lead VCs to have participated in the first or second rounds since the lead VCs usually originate the deal and are among the first venture investors in startups.

In each year, we define VC reputation using the market share of the amount of funds raised by the VC up to the current year since 1975, following the methodology of Megginson and Weiss (1991) and Chemmanur, Krishnan, and Nandy (2011).[55] This measure effectively captures reputation since reputation is primarily built on past success: VCs are usually able to raise greater follow-on funds from their limited partners only if the performance of their funds has been successful in the past. For each VC-backed IPO in our sample, we then calculate the average reputation of their lead VC investor(s). *High-Rep-VC-Backing* is a dummy variable equal to 1 if the average market share of funds raised by their lead VC investors is above the 75th percentile of the sample and 0 otherwise; while *Low-Rep-VC-Backing* is a dummy variable equal to 1 if the average market share of funds raised is equal to or below the 75th percentile of the sample and 0 otherwise.

2.4.3 Measures for Valuation

We measure the valuation of firms at IPO and in the secondary market using a comparable firm approach based on a non-IPO industry peer with comparable Sales and EBITDA profit margin (EBITDA/Sales): see, e.g., Kim and Ritter (1999) and Purnanandam and Swaminathan (2004). To pick an industry peer firm for an IPO firm in our sample, we first consider all firms in the Compustat that were active and present on CRSP for at least

[55] In untabulated tests, we use an alternative measure for VC reputation. We define VC reputation using the market share of the amount of investment made by a VC up to the current year since 1975 and obtain qualitatively similar results.

three years at the end of the fiscal year preceding the IPO. We then eliminate firms that are REITs, closed-end funds, ADRs, not ordinary common shares, and firms with stock prices less than $5 at the report date. We separate the remaining population of Compustat firms into 48 industry groups based on the industry classification introduced by Fama and French (1997). For each year, we divide each industry portfolio into three portfolios based on sales, and then separate each sales portfolio into three portfolios based on EBITDA profit margin (EBITDA/Sales). This procedure gives us nine portfolios for each industry-year.[56] Each IPO firm is then placed into an appropriate year-industry-Sales-EBITDA margin portfolio based on an IPO firm's sales and EBITDA in the year prior to IPO. Within the portfolio, we find a matching firm that is closest in sales to the IPO firm being valued. We are able to find matching firms for 3100 IPO firms (1442 VC-backed and 1658 non-VC-backed IPO firms) in our baseline sample. We then estimate the relative valuation of the IPO firms to their matching firm based on their price multiples.

We measure the relative valuation of an IPO firm at offer (*RVO*) using the following formula:

$$RVO = \frac{\frac{\text{Offer Price} \times \text{IPO firm shares outstanding}}{\text{IPO firm prior fiscal year sales}}}{\frac{\text{Matching firm market price} \times \text{Matching firm shares outstanding}}{\text{Matching firm prior fiscal year sales}}}, \qquad (2.1)$$

In the above, the *Offer Price* of the IPO firm is collected from the SDC database. *IPO firm shares outstanding* refers to the shares outstanding of the IPO firm at the first secondary market trading day as recorded in CRSP. *Matching firm market price* is the stock price and *matching firm shares outstanding* is the number of shares outstanding of the matching firm at the close of the day closest to the IPO offer date.

We measure the relative valuation of an IPO firm in the secondary market using the following formula:

[56] We insist, however, that at least three firms should be in each portfolio. If the number of firms in the industry does not allow us to form 9 portfolios, we limit the separation to two portfolios based on Sales with further separation into two portfolios based on EBITDA profit margin.

$$RVS_t = \frac{\frac{\text{Secondary Market Price} \times \text{IPO firm shares outstanding}}{\text{IPO firm prior fiscal year sales}}}{\frac{\text{Matching firm market price} \times \text{Matching firm shares outstanding}}{\text{Matching firm prior fiscal year sales}}}, \tag{2.2}$$

In the above, the relative valuation in the secondary market in the t-th year after IPO as shown in formula (2), RVS_t, is computed in a similar way: we substitute the IPO offer price and the number of shares outstanding of the IPO firm in formula (1) by the secondary market price in the t-year after IPO and the number of shares outstanding observed on that date in CRSP. Here t equals 0, 1, 2, and 3, and year 0 means at the close of the first trading day in the secondary market. Due to their right skewed distribution, we use the natural log of the above two measures (*Ln(RVO)* and *Ln(RVS$_t$)*) as the dependent variables in our regressions.[57]

In addition to the above relative valuation measures, we use industry-adjusted Tobin's Q as alternative measures for IPO and secondary market valuations. Tobin's Q is defined as the ratio of a firm's market value of assets over its book value of assets, where 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 multiplied by the relevant share price. We measure Tobin's Q at IPO using the IPO offer price as the share price in the above definition, while we measure Tobin's Q in the secondary market using the closing price on the first trading day. The number of shares outstanding for IPO firms is measured as of the first trading day in the secondary market. In untabulated analyses, we obtain quantitatively and qualitatively similar results using these alternative firm valuation measures.

[57] Although our main measures of IPO and secondary market valuations are computed based on Price-to-Sales multiple, we also compute valuation measures based on price-to-EBITDA and price-to-earnings multiples.

2.4.4 The Participation of Financial Market Players

We obtain the institutional investor data from the Thomson Reuters Institutional Holdings (13F) Database, as reported on Form 13F filed with the SEC. All investment companies and professional money managers with assets over $100 million under management are required to report the 13F filings on a quarterly basis. The number of institutional investors (*N_Inst*) is defined as the number of institutions that hold the stocks of the IPO firm at the end of the first fiscal year after IPO. We obtain analyst coverage data from Institutional Brokers Estimate System (I/B/E/S). The analyst coverage measure we use, *N_An*, is defined as the number of analysts providing earnings forecasts at the end of the first fiscal year after IPO. As reported in Table 1, the medians of *N_Inst* and *N_An* are 20 and 3, respectively, suggesting that 20 institutional investors invested in the equity of a typical IPO firm in our sample and three financial analysts provided earnings forecast for a typical IPO firm.

Since the distribution *N_Inst* and *N_An* are right skewed, we use take logs of these two values and use the logged number of institutional investors and that of financial analysts (*Ln(N_Inst)* and *Ln(N_An)*) in our regressions in later sections.

2.4.5 Control Variables

In our regressions in the later sections, our dependent variables include various IPO characteristics as well as investor attention (as proxied by pre-IPO media coverage). Following the existing literature, our control variables include the Carter-Manaster rank of the lead underwriter (*CM Rank*), the natural log of the firm's pre-IPO assets (*Ln(Asset)*), and the fraction of firm equity sold in the IPO (*Fraction Sold*). We obtain the values of pre-IPO assets and the fraction of equity sold in an IPO from the SDC database, or Compustat if the SDC data item is not available. The Carter-Manaster rank of lead underwriter reputation is collected from Jay Ritter's website (http://site.warrington.ufl.edu/ritter/ipo-data/). In addition to the above control variables, we also include industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange (in which the

IPO firm is listed) fixed effects to control for differences among IPO characteristics across different industries, time periods, and listing exchanges in all regressions unless otherwise specified.

2.5 Analysis of the Relation between VC-Backing and Investor Attention

2.5.1 Baseline Analysis of the Relation between VC-Backing and Investor Attention

In this section, we directly test whether VC-backed firms receive greater investor attention (as proxied by pre-IPO media coverage) compared to non-VC-backed firms (**H1**), and whether this effect is stronger for IPO firms backed by high-reputation VCs (**H2**). To test the former hypothesis, we thereby regress our media coverage variables as described in Section 2.4.1, on *VC-Backing*, a dummy variable equal to 1 if the IPO is VC-backed and 0 otherwise. To test the latter hypothesis, we regress our media coverage variables on *High-Rep-VC-Backing* and *Low-Rep-VC-Backing*, dummy variables indicating IPO firms backed by high-and low-reputation VCs, respectively, and test whether the differences between the coefficients on these two variables are statistically different from zero. Our control variables include underwriter reputation (*CM Rank*), pre-IPO assets (*Ln(Asset)*), and the fraction of firm equity sold in the IPO (*Fraction Sold*). We include IPO year dummies, industry dummies based on Fama French 48 industry classifications, and dummies for stock exchange in which the IPO firm is listed to control for the time-invariant, industry-specific, and stock exchange-specific characteristics that might affect the media coverage received by an IPO firm, in all regressions (unless otherwise specified). Standard errors are clustered at the industry level for all regressions in this paper.

We report the effect of VC-backing on investor attention as measured by pre-IPO media coverage in Panel A of Table 2 and the differential effects of high-reputation and low-reputation VC-backing in Panel B. As shown in Panel A, the coefficients of *VC-Backing* are positive and statistically significant at the 1% level in all specifications. Further, the economic magnitude of the effect of VC-backing is significant: for example, Columns (1) and (2) indicate that VC-backing is associated with an increase of 14.1% in the number of headlines covering the IPO firm and an increase of 14.9% in the number of articles. As for control variables, we find that IPO firms underwritten by higher-ranked underwriters and firms that have larger pre-IPO assets are associated with greater pre-IPO media coverage. Collectively, these findings support our hypothesis **H1**. In Panel B, we find that the coefficients of *High-Rep-VC-Backing* are significantly positive at the 1% level in all specifications and are significantly larger than those of *Low-Rep-VC-Backing* as suggested by tests of differences on the coefficients of these two variables shown in the bottom row of Panel B. This provides strong evidence supporting our conjecture that the effect of VC-backing on investor attention is stronger for high-reputation VC-backed IPOs than for low-reputation VC-backed IPOs. These empirical findings are consistent with our hypothesis **H2**.

2.5.2 Instrumental Variable Analysis of the Relation between VC-Backing and Investor Attention

VC-backing and investor attention may be endogenous for the following reason: unobservable firm characteristics (such as firm intrinsic value or firm quality) may affect VC-backing as well as investor attention, so that the greater investor attention we document above for VC-backed firms may be due to the underlying firm characteristics rather than due to VC-backing itself. In order to address the above endogeneity concern, we use an instrumental variable (IV) analysis. In our IV analysis, we instrument for *VC-Backing* using a plausibly exogenous shock to the supply of venture capital.

In doing the above, we broadly follow the methodology of Samila and Sorenson (2011), who use a similar instrument to study the effect of venture capital in fostering innovation and the creation of new firms. Similar to Samila and Sorenson (2011), our instrument is motivated by the following facts. First, institutional investors who are limited partners (LPs) of the VC funds generally adopt an investing strategy that has a fixed optimal asset allocation ratio to distribute their investment over asset classes. For example, they may invest 60% in equity, 30% in fixed income, and 10% in alternative assets (such as venture capital, private equity, and hedge funds). The managers of these LPs regularly rebalance their portfolio to maintain allocation close to the fixed optimal ratio. When the endowments they manage earn higher returns, they are likely to shift assets to venture capital to maintain their asset allocations. Second, these LPs exhibit a "home bias" when investing in venture capital, i.e., they tend to invest in venture capital funds headquartered close to them, we would expect a highly positive correlation between the lagged endowment returns earned by LPs and investments in VC funds whose headquarters are geographically close the LPs.[58] Finally, it has been well documented that VC funds have a strong tendency to invest locally (see, e.g., Sorenson and Stuart (2001)). Venture capitalists rely on social networks to find investments and must travel to their portfolio companies to monitor and advise them. Therefore, VCs tend to prefer to invest in firms that are close to them. Collectively, the above facts imply that higher endowment returns earned by LPs are likely to lead to more venture capital investments in firms in the same states as the LPs in the next few years.

Therefore, we construct our instrument for *VC-Backing*, namely, *LP Returns*, by multiplying the national average returns to college and university endowments (an important class of LPs) by the number of all LPs in each state that had invested in any venture capital fund at least ten years earlier. Specifically, *LP Returns* for firms headquartered in state s in year t is constructed using the following formula:

$$LP\ Returns_{s,t} = \sum_{j=t-10}^{t-1} Endowment\ Returns_j \times Ln(1 + LP_{s,j}), \tag{2.3}$$

[58] As Samila and Sorenson (2010 and 2011) argue, the assumption of "home bias" is likely to hold for a number of reasons: institutional investors might feel more comfortable investing near home, and they might have had prior interactions with the managers of local funds.

where *Endowment Returns*$_j$ is the returns to college and university endowments in year j. We obtained the average annual returns data for college and university endowments, from the website of the National Association of College and University Business Officers.[59] $Ln(1 + LP_{s,j})$ is the log of the number of LPs located in state s who had invested in any venture capital fund at least ten years prior to year j: this data is collected from the SDC Platinum database. The ten-year lag is meant to remove any endogeneity that might result from LPs initiating investment in venture capital in response to a change in local economic conditions. The product of the two provides an estimate of the investment gains that LPs in a given state experience and hence of the amount of funds available for investments in VC funds. As shown in (2.3), we then summed up ten years of inflows into VC funds prior to the IPO year to create our instrument for the VC-Backing of an IPO firm.[60]

We report our 2SLS results for the effect of VC-backing on investor attention (as proxied by pre-IPO media coverage) in Table 3. Since our endogenous variable is binary, we use a probit model in the first stage and regress *VC-Backing* on our instrument *LP Returns* controlling for the same set of control variables and fixed effects as described in earlier sections, following Wooldridge (2010). In the second stage, we use the predicted probability of VC-backing from the first stage as an instrument. We report the first-stage result in Column (1) of Table 3. Consistent with our earlier conjecture, we find that the coefficient of *LP Returns* is significantly positive, suggesting that higher endowment returns earned by LPs lead to greater chances of VCs backing private firms in the same state in the next few years. In Column (1), we also report the Kleibergen-Paap *rk* Wald statistic (Kleibergen and Paap (2006)), which directly tests whether our instrument predicts a sufficient amount of the variance in the endogenous variable to identify our equations. Stock and Yogo (2005) report a critical value of 16.38 for the IV estimates to have no more than 10% of the bias of the OLS estimates for LIML estimation with one instrument and one endogenous variable

[59]See more details at http:www.nacubo.org.

[60]In untabulated results, we also construct our instrument by summing up the inflows of investment into VC funds from five years prior to ten years prior. The results are qualitatively similar.

and ours is 29.93, which is significantly larger than the critical value.

Columns (2)-(3) report the second-stage results of the effect of *VC-Backing* on pre-IPO media coverage variables. In each specification, the coefficient of *VC-Backing* is significantly positive and gets even larger compared to the OLS regression estimates as in Table 2, suggesting that the positive relationship between VC-backing and investor attention around a firm's IPO that we documented in our baseline analysis is causal.

2.6 Analysis of the Relation between VC-Backing, Investor Attention, and IPO Characteristics

2.6.1 VC-Backing, Investor Attention, and Price Revision

In this section, we study the relationship between VC-backing, investor attention (as proxied by pre-IPO media coverage), and the IPO offer price revision, which corresponds to our hypotheses **H3A** and **H3B**. We run the following regression:

$$Ln(PR) = \alpha + \beta\, VC\text{-}Backing + \gamma Z + year\ FE + industry\ FE + stock\ exchange\ FE + \epsilon, \quad (2.4)$$

where the dependent variable, *Ln(PR)*, is the natural log of one plus the absolute value of difference between the IPO offer price and the midpoint of the original filing range.

We present our empirical results for the above test in Table 4. Columns (1) reports the regression result of *Ln(PR)* on the dummy variable for VC-backing. We find that the coefficient of *VC-Backing* is positive and significant at the 1% level. The economic magnitude is significant as well: VC-backing is associated with 0.014 increase in the *Ln(PR)*, which is equivalent to 14% of the median *Ln(PR)*. These findings suggest a positive relationship between VC-backing and the absolute value of the IPO offer price revision, which is consistent with the information extraction hypothesis **H3A**. Columns (2) and (3) present regression results of the IPO offer price revision on the two media coverage variables, *Ln(Headlines)* and *Ln(Articles)*, respectively. The coefficients on *Ln(Headlines)* and *Ln(Articles)* are positive and significant at the 1% level, suggesting that greater investor attention is associated with a greater absolute value of IPO offer price revision.[61]

As we argued in earlier sections, under the information extraction hypothesis, we would expect VC-backed IPO firms receiving a higher level of investor attention to be associated with a larger absolute value of IPO offer price revision, even after controlling for the direct effect of VC-backing. To test this conjecture, we include the interaction of *VC-Backing* and a dummy variable for greater investor attention (namely, *High Headlines*) and test the following model:

$$\begin{aligned} Ln(PR) =& \alpha + \beta \, \textit{VC-Backing} + \lambda High\ Headlines + \theta \, \textit{VC-Backing} \times High\ Headlines \\ & + \gamma Z + year\ FE + industry\ FE + stock\ exchange\ FE + \epsilon. \end{aligned} \tag{2.5}$$

Columns (4) and (5) of Table 4 report the results for these interaction tests. We find that the coefficients of the interaction terms, *VC-Backing*×*High Headlines* and *VC-Backing*×*High Articles*, are significantly positive. Consistent with the information extraction hypothesis, these findings suggest that VC-backed firms that have attracted greater investor attention around their IPOs are likely to have even larger price revisions.

2.6.2 VC-Backing, Investor Attention, and Secondary Market Valuation

In this section, we analyze the effect of VC-backing on the post-IPO immediate secondary market valuations of IPO firms and the channel through which this may happen, corresponding to our hypothesis **H4**. We begin our analysis with a univariate comparison of median firm valuations in the immediate secondary market between VC-backed and non-VC-backed

[61]When we report our regression results of the relation between investor attention and price revision, we tabulate only the results for the continuous versions of these variables: i.e., *Ln(Headlines)* in Column (2) and *Ln(Articles)* in Column (3). In untabulated results, we find that similar results hold when we measure investor attention using dummified versions of these variables: i.e., *High Headlines* and *High Articles*. We take a similar approach in reporting the results of our analysis of all other IPO characteristics, such as secondary market and IPO valuations and IPO initial returns: i.e., we report regression results using only the continuous versions of our two investor attention variables, though these results hold for the dummified versions of these variables as well.

firms. Though our main measures of secondary market valuation (and IPO market valuation as well) are computed based on the price-to-sales multiple, we also compute valuation measures based on price-to-EBITDA and price-to-earnings multiples, compare their medians between VC-backed and non-VC-backed subsamples, and find that these results are consistent with our results using measures based on the price-to-sales multiple. We present these univariate analysis results in Table 5.

Our univariate results in Panels A-C of Table 5 show that the VC-backed firms have significantly higher valuation in the post-IPO immediate secondary market compared with non-VC-backed firms. The differences in the median valuations between VC-backed and non-VC-backed firms are significant both statistically (all at the 1% level) and economically. A consistent pattern is observable across different decades, suggesting that our results are not driven by a particular period of time.[62]

We then move on to assess the relationship between VC-backing and secondary market firm valuations by running multivariate regressions. We adopt the same regression models as (2.4)-(2.5) in Section 2.6.1 but use *Ln*(RVS_0), our measure of secondary market valuation of an IPO firm relative to an industry peer, as the dependent variable.

Our results for the above multivariate regressions are reported in Table 6. Column (1) shows that the coefficient of VC-backing is positive and statistically significant at the 1% level. In terms of economic magnitude, VC-backing is associated with a 36.9% increase in RVS_0. Columns (2) and (3) present the effect of our investor attention proxies, *Ln(Headlines)* and *Ln(Articles)*, respectively. We find that our investor attention proxies by themselves have a significantly positive effect on the post-IPO immediate secondary market valuations, which is consistent with the theoretical prediction of Merton (1987) and the empirical findings of Liu, Sherman, and Zhang (2014). With regard to control variables, we find IPO firms with more reputable underwriters and a smaller fraction of firm equity sold to the public have

[62] In untabulated results, we compare the median valuation of VC-backed and non-VC-backed IPO firms on a yearly basis and find that VC-backed firms have consistently higher valuations than non-VC-backed firms. These results are not reported to conserve space and are available from the authors upon request.

higher valuations, which is consistent with the existing IPO literature. Columns (4) and (5) summarize the results for the interaction tests. We find that in both specifications, the coefficients of the interaction terms (*VC-Backing*×*High Headlines* and *VC-Backing*×*High Articles*) are significantly positive, suggesting that there is an incremental positive effect of greater investor attention received by VC-backed firms on immediate post-IPO secondary market valuations, even after controlling for the direct effect of VC-backing. Collectively, our empirical results provide strong evidence consistent with our hypothesis **H4**.

2.6.3 VC-Backing, Investor Attention, and IPO Market Valuation

We now turn to the study of the relationship between VC-backing and IPO market valuations, which corresponds to our hypotheses **H5A** and **H5B**. As in the prior section, we begin our analysis with a univariate comparison of the median IPO market valuations between VC-backed and non-VC-backed firms using valuation measures based on price-to-sales, price-to-EBITDA, and price-to-earnings multiples. We present these results in Panels D-F of Table 5. We find that the median IPO market valuations are significantly higher for VC-backed firms than for non-VC-backed firms. The differences of median IPO valuations between VC-backed and non-VC-backed IPO firms are significant statistically (mostly at the 1% level) as well as economically. A similar pattern remains persistent across different decades.

We then conduct multivariate regressions to test the relation between VC-backing, investor attention, and IPO market valuations. We adopt the same regression models as in Section 2.6.2, but use the IPO market valuation measure, *Ln(RVO)*, as the dependent variable. We report the results for these tests in Table 7. Column (1) shows that the coefficient of *VC-Backing* is positive and significant both statistically and economically: *VC-Backing* is associated with a 32.5% increase in *RVO*. In Columns (4) and (5), we report the results for our interaction tests. We find that the coefficients on *VC-Backing*×*High Headlines* is positive and significant at the 1% level, while the coefficient on *VC-Backing*×*High Articles* is positive but insignificant. These results provide evidence for the conjecture that VC-backed firms receiving higher investor attention are associated with higher valuations at the offer price even after controlling for the direct effect of VC-backing. In general, the above findings lend support for our hypothesis **H5A**.

2.6.4 VC-Backing, Investor Attention, and IPO Initial Returns

We now move on to the study of the relationship between VC-backing and IPO initial returns, as captured by our hypotheses **H6A** and **H6B**. To assess the effect of VC-backing on IPO initial returns, we regress *Initial Ret*, which is defined as the percentage change from the offer price to the first-day closing price in the secondary market, on the VC-backing dummy, investor attention measures as proxied by pre-IPO media coverage, and the interaction of the VC-backing dummy and dummies for greater media courage, namely, *High Headlines* and *High Articles*.

We present the results of the above tests in Table 8. Our results show that VC-backing has a significantly positive effect on IPO initial returns as presented in Column (1). The economic magnitude is significant as well: on average, VC-backing is associated with a 4.5% increase in IPO initial returns, which is equivalent to 22.6% of the sample mean. Columns (2) and (3) show that both media coverage variables, *Ln(Headlines)* and *Ln(Articles)*, are significantly and positively related to the initial returns, suggesting that firms that have attracted more investor attentions have higher initial returns. Columns (4) and (5) present the regression results using *VC-Backing* $\times$ *High Headlines* and *VC-Backing* $\times$ *High Articles* as the main explanatory variables, respectively. We find that the coefficient of each of these interaction terms is positive and significant at the 1% level, while the coefficient of *VC-Backing* becomes insignificant. These findings suggest that there is an incremental positive effect of greater investor attention on IPO initial returns, even after controlling for the direct effect of VC-backing. Collectively, these findings support our hypothesis **H6B**.

2.6.5 VC Reputation, Investor Attention, and IPO Characteristics

We now turn to the study of the relationship between the reputation of lead VC investors backing an IPO firm, investor attention, and various IPO characteristics such as the secondary market and IPO firm valuations, and IPO initial returns. We test the following model:

$$\begin{aligned} Dep\ Var = {} & \alpha + \theta_1 \textit{High-Rep-VC-Backing} \times High\ Headlines \\ & + \theta_2 \textit{Low-Rep-VC-Backing} \times High\ Headlines + \beta_1 \textit{High-Rep-VC-Backing} \\ & + \beta_2 \textit{Low-Rep-VC-Backing} + \lambda High\ Headlines + \gamma Z \\ & + year\ FE + industry\ FE + stock\ exchange\ FE + \epsilon. \end{aligned} \tag{2.6}$$

We interact the two dummy variables for high-reputation and low-reputation VC-backing with *High Headlines* (or *High Articles*) and use these interactions terms as the main explanatory variables in our regressions. Following our discussion in 2.3.3, we expect θ_1 to be significantly positive and larger than θ_2.

We report our regression results for the relationship between VC reputation, investor attention, and IPO characteristics in Table 9. Column (1), (4), and (7) report regression results that use *High-Rep-VC-Backing* and *Low-Rep-VC-Backing* as the main explanatory variables. We find that the effect of high-reputation VC-backing on IPO initial returns is significantly larger than that of low-reputation VC-backing. The rest of Table 9 report the results for our interaction tests. As shown in Columns (2), (5), and (8), the coefficients of *High-Rep-VC-Backing*×*High Headlines* are significantly positive and significantly larger than those of *Low-Rep-VC-Backing*×*High Headlines* in the regressions for immediate post-IPO secondary market valuation, IPO valuation, and initial returns. Our regressions using the interaction terms between reputation variables and *High Articles* (as in Column (3), (6), and (9)) provide qualitative consistent but weaker results. In general, our findings suggest that high-reputation VC-backed IPO firms receiving greater investor attention have higher valuations in the secondary and IPO markets as well as higher initial returns compared to low-reputation VC-backed IPO firms receiving greater investor attention. Thus the results reported in this section provide additional support for our hypotheses **H4**, **H5A**, and **H6B**.

2.6.6 VC-Backing, Investor Attention, and Financial Market Player Participation

In this section, we study how VC-backing affects the participation of financial market players (institutional investors and financial analysts) in the IPO and in the immediate post-IPO secondary market using multivariate regression analyses. Our dependent variables are the natural log of the number of institutional investors holding the stock of the IPO firm (*Ln(N_Inst)*) and the natural log of the number of analysts following the IPO firm (*Ln(N_An)*) at the end of the first fiscal year after IPO.

Table 10 reports our findings on the participation of institutional investors in the IPO. Column (1) reports the effect of VC-backing on the number of institutional investors holding the stock of the IPO firm. We find VC-backing is positively associated with the number of institutional investors. In terms of economic magnitude, VC-backing is associated with a 21.2% increase in the number of institutional investors. Columns (2) and (3) report the effect of our investor attention proxies, *Headlines* and *Articles*, on the number of institutional investors, respectively. We find that the coefficient of each of these proxies is positive and significant, consistent with Merton's (1987) attention model as well as with Liu, Sherman, and Zhang (2014)'s empirical findings. In Columns (4) and (5), we report the results for our interaction tests. We find the coefficient of *VC-Backing* × *High Headlines* is positive and significant at the 10% level, while that of *VC-Backing* × *High Articles* is positive but insignificant. This provides evidence for our conjecture that there is an incremental positive effect of higher investor attention received by VC-backed firms on institutional investor participation, even after controlling for the direct effect of VC-backing. As for control variables, pre-IPO firm size and underwriter rank are positively related to the number of institutional investors holding the equity of the firm, while the fraction of equity sold in the IPO is negatively related to the number of institutional investors. These empirical findings are consistent with our hypothesis **H7**.

In Table 11, we turn to study the relationship between VC-backing, investor attention, and the number of analysts following the IPO firm. We find that VC-backing remains positively and significantly related to analyst coverage as shown in Column (1): VC-backing increases analyst coverage by 13.6%. In Columns (2) and (3), we find that each of our investor attention proxies is significantly and positively related to analyst coverage, indicating higher pre-IPO investor attention is likely to lead to greater analyst coverage immediately after IPO. In Columns (4) and (5), we find that the coefficient of *VC-Backing* $\times$ *High Headlines* is positive and significant at the 10% level, while that of *VC-Backing* $\times$ *High Articles* is positive but insignificant. This provides evidence consistent with our conjecture that there is an incremental positive effect of higher investor attention received by VC-backed firms on analyst coverage, even after controlling for the direct effect of VC-backing. Collectively, the above results are consistent with our hypothesis **H8**.

2.6.7 The Dynamics of Investor Attention and Secondary Market Valuation

In this section, we study the dynamics of IPO firms' secondary market valuations over time, from the close of the first trading day in the secondary market up to three years after IPO, corresponding to our hypotheses **H9** and **H10**. We first conduct a univariate analysis of the secondary market valuations over time for VC-backed and non-VC-backed subsamples. Table 12 reports the median valuations in the secondary market at the close of the first trading day, as well as in one, two, and three years following the IPO date for VC-backed and non-VC-backed IPO firms. Panel A presents the results using our main valuation measures, which are computed based on the price-to-sales ratio. Panels B and C use alternative valuation measures that are computed based on the price-to-EBITDA and price-to-earnings ratio, respectively. The last two columns of all panels test the statistical differences in median valuations between VC-backed and non-VC-backed subsamples.

For all three panels, we find consistent results that VC-backed IPO firms have higher secondary market valuations compared to non-VC-backed firms at the close of the first trading day, as well as in one, two, and three years after IPO. The differences in medians between VC-backed and non-VC-backed subsamples are statistically significant, mostly at the 1% level. Within each panel, we find that the median valuations decrease over time for both VC-backed and non-VC-backed firms. Moreover, VC-backed firms tend to have a larger decrease in valuations over time compared to non-VC-backed firms. Further, the differences in median valuations between VC-backed and non-VC-backed IPO firms become smaller over time. This pattern is also depicted in Figure 2, in which we plot the medians of secondary market valuations over time for VC-backed and non-VC-backed subsamples. The upper panel uses the entire sample while the lower panel uses firms that have all three years of data available. Both panels show that the differences in medians between VC-backed and non-VC-backed firms tend to become smaller as time elapses subsequent to IPO.

We then move on to study the dynamics of secondary market valuations in a multivariate regression setting. Specifically, we test the following models:

$$Ln(RVS_t) = \alpha + \beta_1 Time\ Trend + \beta_2 Time\ Trend \times VC\text{-}Backing + Firm\ FE + \epsilon_{i,t}, \tag{2.7}$$

$$\begin{aligned} Ln(RVS_t) = \alpha &+ \beta_1 Time\ Trend + \beta_2 Time\ Trend \times VC\text{-}Backing \\ &+ \beta_3 Time\ Trend \times VC\text{-}Backing \times High\ Headlines \\ &+ \beta_4 Time\ Trend \times High\ Headlines + Firm\ FE + \epsilon_{i,t}. \end{aligned} \tag{2.8}$$

In the above regressions, *Ln(RVS$_t$)* is the IPO firm's valuation in the secondary market in the t-th year after IPO, where t equals 0, 1, 2, and 3, and year 0 means at the close of the first trading day in the secondary market. *Time Trend* is a linear time trend, defined as the number of years after IPO, which equals to 0, 1, 2, or 3. *VC-Backing* is a dummy variable indicating that a firm is VC-backed. *High Headlines* (*High Articles*) is a dummy variable indicating that the number of headlines (articles) covering the IPO firm in the two months prior to the IPO date is above the sample median. We include the full expansion of the triple interaction of *Time Trend*, *VC-Backing*, and *High Headlines* (or *High Articles*) in regression (2.8).[63] In order to alleviate the concern that our regression results for the dynamics of secondary market valuations may be affected by intrinsic value or quality of the firm, we include firm fixed effects in the above regressions to control for firms' intrinsic value, which may be driven, for example, by VC-backed firms being of different quality than non-VC-backed firms. Standard errors are clustered at the industry level in the above regressions. The coefficients of our interest are β_2 and β_3.

We present our results for the above regressions in Panel A of Table 13. In Column (1), we regress our measure for secondary market valuation, $Ln(RVS)_t$, on time trend only and find that there is a significant and negative relationship between the two, justifying the inclusion of this variable in all the regressions reported in this table. In Column (2), we include the interaction term of *Time Trend* and *VC-Backing* as the main explanatory variable. We find that the coefficient on this interaction term, β_2, is negative and significant at the 1% level, which suggests that the valuation of VC-backed IPO firms will fall to a greater extent than that of non-VC-backed firms and is consistent with our hypothesis **H9**. In the last two columns, we further include the triple interaction term, *Time Trend*×*VC-Backing*×*High Headlines* (*High Articles*). The coefficients of *Time Trend* and of *Time Trend*×*VC-Backing* are significantly and negatively related to secondary market valuation. Further, the coefficient (β_3) of *Time Trend*×*VC-Backing*×*High Headlines* (*High Articles*) is negative in both Columns (4) and (5), with the one in Column (5) being statistically significant at the 10% level. This provides evidence that VC-backed firms receiving greater investor attention are likely to experience larger decreases in valuations over time in the secondary market. The above empirical findings are consistent with our hypothesis **H10**.

[63] *VC-Backing*, *High Articles*, *High Headlines*, *VC-Backing*×*High Articles*, and *VC-Backing*×*High Headlines* are absorbed by the firm fixed effects in this specification.

To study the impact of high-reputation versus low-reputation VC-backing on the dynamics of secondary market valuations, we interact *High-Rep-VC-Backing* and *Low-Rep-VC-Backing* with *Time Trend* and *High Headlines* (*High Articles*) and report the results for these interaction tests in Panel B of Table 13. In Column (1), our evidence suggests that both high-reputation and low-reputation VC-backed IPO firms experience a fall in valuations as time passes, but there is no significant difference in the decreases in valuation between high-reputation and low-reputation VC-backed firms. In Column (2), we find that the coefficient of *Time Trend*×*High-Rep-VC-Backing*×*High Headlines* is negative and significant. Further, the coefficient of *Time Trend*×*High-Rep-VC-Backing*×*High Headlines* is larger in magnitude than that of *Time Trend*×*Low-Rep-VC-Backing*×*High Headlines*. In Column (3), we find qualitatively similar but weaker results using the interaction of time trend, VC reputation dummies, and the article variable. The above empirical results suggest that IPO firms backed by high-reputation lead VCs that have attracted higher investor attention are likely to experience larger decreases in valuation over time than IPO firms backed by low-reputation lead VCs that have attracted higher investor attention, consistent with the investor attention channel of VC value creation in the IPO market.

2.6.8 Instrumental Variable Analysis: VC-Backing, Investor Attention, and IPO Characteristics

Our OLS regression results show that VC-backed IPO firms are associated with higher absolute values of price revision, have higher IPO and secondary market valuations, and higher IPO initial returns. We also show that VC-backed IPO firms have greater participation by institutional investors and have greater post-IPO analyst coverage. However, as argued earlier in Section 2.5.2, VC-backing and IPO characteristics may be endogenous. In particular, unobservables (such as the intrinsic value of the firm going public) may affect VC backing as well as IPO characteristics, so that the favorable IPO characteristics that we documented earlier for VC-backed firms may be due to underlying firm characteristics rather than due to VC-backing itself. We therefore use the instrument (*LP Returns*) that we documented in Section 2.5.2 for VC-backing to conduct an instrumental variable analysis to account for the above endogeneity concern.

We report the second-stage results of our IV regression analysis for the effect of VC-backing on a variety of IPO characteristics (including IPO offer price revision, secondary market valuation, IPO market valuation, IPO initial returns, institutional investor participation, and financial analyst coverage) in Table 14. After controlling for the potential endogeneity of *VC-Backing* and IPO characteristics using our IV analysis, we continue to find a highly positive relationship between *VC-Backing* and each of the above dependent variables: the coefficient on *VC-backing* is positive and significant at the 1% level for all of our second-stage regressions. These findings suggest that the relations between VC-backing and the above favorable IPO characteristics are causal.

We have established using the above IV analysis in this section that VC-backing causally affects IPO characteristics such as IPO and immediate secondary market valuations and IPO initial returns. We now turn to the channel through which this causal effect operates. As we showed using our OLS analysis of various IPO characteristics and our dynamic analysis of post-IPO secondary market valuations, we argue here that at least one channel through which this causal effect operates is through investor attention. In this context, we note that we have already established (using our IV analysis presented in Section 2.5.2) a positive causal relationship between VC-backing and investor attention. Further, Liu, Sherman, and Zhang (2014) has established (using an IV analysis where they use the number of special news reports aired on the three major US television networks (ABC, CBS, and NBC) as an instrumental variable for investor attention) that investor attention is positively and causally related to IPO characteristics such as the IPO firm's long-term stock value.[64] In untabulated results, we have conducted a similar IV analysis using the number of special

[64]Liu, Sherman, and Zhang (2014) argue that these special news reports were exogenous events that drew attention away from any IPO firms that were trying to attract a following and thus the number of these special news reports is a valid instrumental variable for investor attention as proxied by media coverage. See more details about the justification of this instrument in their paper.

news reports aired on the three major US television networks (ABC, CBS, and NBC) in the two months prior to IPO as an instrument for investor attention and find that investor attention is causally related to offer price revision, IPO and secondary market valuations, IPO initial returns, institutional investor participation, and post-IPO analyst coverage.[65] Taken together, these two results imply that at least one channel through which the causal effect of VC-backing on IPO characteristics operates is by enhancing the investor attention garnered by the IPOs of firms backed by them.

2.7 Conclusion

We propose and empirically analyze a new channel through which VCs may create incremental value at the time of IPO for the entrepreneurial firms that they invest in. We hypothesize that the IPOs of VC-backed firms garner greater "investor attention" (in the sense of Merton (1987)), allowing the IPO underwriters of such firms to perform two information-related roles more efficiently during the IPO book-building and road-show process: information dissemination, where the lead underwriter disseminates noisy information about various aspects of the IPO firm to institutional investors; and information extraction, where the lead underwriter extracts information useful in pricing the IPO firm equity from institutional investors. Based on this investor attention channel, we develop testable implications for the IPO characteristics of VC-backed firms and empirically test these implications. Using a hand-collected dataset of pre-IPO media coverage as a proxy for investor attention, we first show that the IPOs of VC-backed firms indeed attract greater investor attention than those of non-VC backed firms. Further, while the IPOs of high- and low-reputation VC-backed firms attract greater investor attention than non-VC-backed firms, the IPOs of high-reputation VC-backed firms attract greater investor attention than those of low-reputation VC-backed firms. We find that VC-backed firms are associated with larger absolute values of IPO offer price revisions; greater IPO and after-market valuations; larger IPO initial returns; greater

[65] Given space constraints, we choose not to present these results here. These results are available from the authors upon request.

institutional investor equity holdings; and greater analyst coverage immediately post-IPO. Our dynamic analysis of IPO firm valuation in the three years post-IPO shows that the valuation of VC-backed firms falls to a greater extent than those of non-VC backed firms corresponding to investor attention fading with time, with the valuation of those VC-backed firms that received the greatest investor attention at IPO falling to the greatest extent. Our instrumental variable analysis shows that the positive relation we document between VC-backing, investor attention, and various IPO characteristics is causal.

References

Amornsiripanitch, Natee, Paul A. Gompers, and Yuhai Xuan, 2016, More than money: Venture capitalists on boards, Working paper, Havard Business School.

Bereskin, Frederick L., and Po-Hsuan Hsu, 2013, Bringing in changes: The effect of new ceos on innovation, Working paper, University of Delaware.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend, 2015, The impact of venture capital monitoring, *The Journal of Finance (Forthcoming)* .

Bishara, Norman D., Kenneth J. Martin, and Randall S. Thomas, 2015, An empirical analysis of noncompetition clauses and other restrictive postemployment covenants, *Vanderbilt Law Review* 68, 1–51.

Boot, Arnoud W. A., 1992, Why hang on to losers? divestitures and takeovers, *The Journal of Finance* 47, 1401–1423.

Chemmanur, Thomas J., Lei Kong, Karthik Krishnan, and Qianqian Yu, 2016, Top management human capital, inventor mobility, and corporate innovation, Working paper, Boston College.

Chemmanur, Thomas J., Karthik Krishnan, and Debarshi K. Nandy, 2011, How does venture capital financing improve efficiency in private firms? a look beneath the surface, *Review of Financial Studies* 24, 4037–4090.

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

Cornelli, Francesca, and Oğuzhan Karakaş, 2015, CEO turnover in LBOs: The role of boards, Working paper, LBS.

Cornelli, Francesca, Zbigniew Kominek, and Alexander Ljungqvist, 2013, Monitoring managers: Does it matter?, *The Journal of Finance* 68, 431–481.

Da Rin, Marco, Thomas F. Hellmann, and Manju Puri, 2013, A survey of venture capital research, in George M. Constantinides, Milton Harris, and René M. Stulz, eds., *Handbook of the Economics of Finance*, 573–648 (Elsevier, Amsterdam).

Denis, David J., and Diane K. Denis, 1995, Performance changes following top management dismissals, *The Journal of Finance* 50, 1029–1057.

Ewens, Michael, and Matt Marx, 2014, Executive replacement in venture capital-backed startups, Working paper, Caltech.

Gao, Huasheng, Jarrad Harford, and Kai Li, 2015, CEO turnover-performance sensitivities in private firms, *The Journal of Financial and Quantitative Analysis (Forthcoming)* .

Garmaise, Mark J., 2009, Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment, *Journal of Law, Economics, and Organization* 376–425.

Gorman, Michael, and William A. Sahlman, 1989, What do venture capitalists do?, *Journal of Business Venturing* 4, 231–248.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working Paper 8498, National Bureau of Economic Research.

Hellmann, Thomas, and Manju Puri, 2002, Venture capital and the professionalization of start-up firms: Empirical evidence, *The Journal of Finance* 57, 169–197.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *The Journal of Finance* 62, 251–301.

Huang, Sheng, 2014, Managerial expertise, corporate decisions and firm value: Evidence from corporate refocusing, *Journal of Financial Intermediation* 23, 348–375.

Huson, Mark R., Robert Parrino, and Laura T. Starks, 2001, Internal monitoring mechanisms and ceo turnover: A long-term perspective, *The Journal of Finance* 56, 2265–2297.

Kaplan, Steven N., and Per Strömberg, 2003, Financial contracting theory meets the real world: An empirical analysis of venture capital contracts, *The Review of Economic Studies* 70, 281–315.

Knyazeva, Anzhela, Diana Knyazeva, and Ronald W. Masulis, 2013, The supply of corporate directors and board independence, *Review of Financial Studies* 26, 1561–1605.

Lerner, Josh, 1995, Venture capitalists and the oversight of private firms, *The Journal of Finance* 50, 301–318.

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

Malsberger, Brian M., 2004, *Covenants Not To Compete: A State-by-state Survey* (Bna Books, Washington).

Manso, Gustavo, 2011, Motivating innovation, *The Journal of Finance* 66, 1823–1860.

Marx, Matt, Deborah Strumsky, and Lee Fleming, 2009, Mobility, skills, and the michigan non-compete experiment, *Management Science* 55, 875–889.

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

Oyer, Paul, and Scott Schaefer, 2011, Chapter 20 - personnel economics: Hiring and incentives, volume 4, Part B of *Handbook of Labor Economics*, 1769–1823 (Elsevier).

Pan, Yihui, 2015, The determinants and impact of executive-firm matches, *Management Science (Forthcoming)* .

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

Sörensen, Morten, 2007, How smart is smart money? a two-sided matching model of venture capital, *The Journal of Finance* 62, 2725–2762.

Stock, James H., and Motohiro Yogo, 2005, Testing for weak instruments in linear IV regression, *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* .

Tian, Xuan, 2011, The role of venture capital syndication in value creation for entrepreneurial firms, *Review of Finance* 245–283.

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

Wasserman, Noam, 2003, Founder-CEO succession and the paradox of entrepreneurial success, *Organization Science* 14, 149–172.

Weisbach, Michael S., 1988, Outside directors and CEO turnover, *Journal of Financial Economics* 20, 431–460, The Distribution of Power Among Corporate Managers, Shareholders, and Directors.

Weisbach, Michael S., 1995, CEO turnover and the firm's investment decisions, *Journal of Financial Economics* 37, 159–188.

Wooldridge, Jeffrey M., 2010, *Econometric analysis of cross section and panel data*, second edition (MIT press., Cambridge).

Table 1: Summary Statistics

This table reports the summary statistics for the sample of IPOs in the US from 1980 to 2009. We exclude equity offerings of financial institutions (SIC codes between 6000 and 6999) and regulated utilities (SIC codes between 4900 and 4999), unit offerings, closed-end funds, real estate investment trusts (REITs), American Depositary Receipts (ADRs), rights issues, spin-offs, equity carve-outs, leverage buyouts, tracking stocks, issues with offer price less than $5, issues with incomplete information on offer price and the number of shares filed in an IPO, and duplicates. The IPO firm should issue common shares (with share code headers of 10 and 11 in CRSP). We further require that the issuing firm must be present on the Compustat annual industrial database for the fiscal year prior to the offering and at least for one year after the offering, as well as on the CRSP database within sixty days of the issue date. *Headlines* is the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Articles* is the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *RVO* is the valuation of an IPO firm at offer relative to an industry peer. RVS_0 is the valuation of the IPO firm at the close of the first trading day in the secondary market relative to an industry peer. *Initial Ret* is the percentage change from the offer price to the first-day closing price in the secondary market. *Price Revision* the absolute value of difference between the IPO offer price and the midpoint of original filing range. *N_Inst* is the number of institutions that hold the stocks of the firm at the end of the first fiscal year after IPO. *N_An* is the number of analysts providing earnings forecast at the end of the first fiscal year after IPO. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO.

Variables	N	Mean	Std. Dev	Min	25th	Median	75th	Max
Headlines	4105	4.891	10.229	0.000	0.000	2.000	5.000	272.000
Articles	4105	29.662	94.924	0.000	2.000	9.000	32.000	4369.000
VC-Backing	4105	0.457	0.498	0.000	0.000	0.000	1.000	1.000
RVO	3100	4.629	12.434	0.023	0.774	1.659	3.971	254.512
RVS_0	3100	6.273	19.189	0.026	0.838	1.911	4.773	342.800
Initial Ret	4070	0.199	0.428	-0.705	0.003	0.073	0.229	6.056
Price Revision	3964	0.160	0.176	0.000	0.048	0.105	0.227	2.100
N_Inst	3924	34.524	43.275	1.000	9.000	20.000	46.000	760.000
N_An	3502	4.302	3.561	1.000	2.000	3.000	6.000	43.000
CM Rank	3868	7.186	2.126	0.100	6.000	8.000	9.000	9.000
Ln(Asset)	4006	3.163	1.752	-3.912	2.080	3.077	4.138	11.823
Fraction Sold	4070	0.327	0.212	0.031	0.218	0.291	0.381	7.823

Table 2: VC-Backing and Investor Attention

Panel A reports the OLS regression results of the effect of VC-backing on investor attention around a firm's IPO (as proxied by pre-IPO media coverage); Panel B reports the OLS regression results of the effect of high- and low-reputation VC-backing on investor attention. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *High-Rep-VC-Backing* is a dummy variable equal to 1 if the average market share of funds raised by the IPO firm's lead VC investors is above the 75th percentile of the sample and 0 otherwise. *Low-Rep-VC-Backing* is dummy variable equal to 1 if the average market share of funds raised by the IPO firm's lead VC investors is equal to or below the 75th percentile of the sample and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the industry 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 VC-Backing on Investor Attention (as Proxied by Media Coverage)				
	(1)	(2)	(3)	(4)
VARIABLES	Ln(Headlines)	Ln(Articles)	High Headlines	High Articles
VC-Backing	0.141***	0.149***	0.054**	0.042*
	(0.037)	(0.041)	(0.023)	(0.022)
CM Rank	0.072***	0.108***	0.033***	0.028***
	(0.007)	(0.010)	(0.005)	(0.004)
Ln(Asset)	0.021*	0.071***	0.004	0.019***
	(0.011)	(0.013)	(0.005)	(0.005)
Fraction Sold	-0.114	-0.052	-0.030	-0.015
	(0.100)	(0.069)	(0.040)	(0.017)
Observations	3,696	3,696	3,696	3,696
Adjusted R-squared	0.409	0.664	0.318	0.542
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes

Panel B: The Effect of VC Reputation on Investor Attention (as Proxied by Media Coverage)				
	(1)	(2)	(3)	(4)
VARIABLES	Ln(Headlines)	Ln(Articles)	High Headlines	High Articles
High-Rep-VC-Backing	0.239***	0.246***	0.106***	0.093***
	(0.047)	(0.065)	(0.023)	(0.028)
Low-Rep-VC-Backing	0.112***	0.125***	0.041*	0.030
	(0.036)	(0.042)	(0.023)	(0.022)
CM Rank	0.071***	0.107***	0.032***	0.028***
	(0.007)	(0.010)	(0.005)	(0.004)
Ln(Asset)	0.020*	0.070***	0.003	0.018***
	(0.011)	(0.013)	(0.005)	(0.005)
Fraction Sold	-0.113	-0.051	-0.029	-0.014
	(0.100)	(0.068)	(0.040)	(0.017)
Observations	3,696	3,696	3,696	3,696
Adjusted R-squared	0.410	0.665	0.319	0.543
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes
High-Rep VC- Backing – Low-Rep-VC-Backing	0.127***	0.121***	0.065***	0.063***

Table 3: Instrumental Variable Analysis of the Effect of VC-Backing on Investor Attention

This table reports the Instrumental Variable regression results of the effect of VC-backing on investor attention around a firm's IPO (as proxied by pre-IPO media coverage). Column (1) reports the first stage probit regression result, i.e., regressing *VC-Backing* on our instrument, *LP Returns*, which is defined in Section 2.5.2. Columns (2) and (3) report the second-stage results of the effect of VC-backing on media coverage. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
	1st Stage	2nd Stage	2nd Stage
VARIABLES	VC-Backing	Ln(Headlines)	Ln(Articles)
LP Returns	0.323***		
	(0.116)		
VC-Backing		0.644***	0.692***
		(0.154)	(0.108)
CM Rank	0.219***	0.044***	0.080***
	(0.020)	(0.014)	(0.010)
Ln(Asset)	-0.153***	0.046***	0.099***
	(0.027)	(0.012)	(0.014)
Fraction Sold	-0.543*	-0.014	0.060
	(0.313)	(0.079)	(0.069)
Observations	3,331	3,331	3,331
Pseudo R-squared	0.266		
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes
Kleibergen-Paap rk Wald Stat	29.93		

Table 4: VC-Backing, Investor Attention, and Offer Price Revision

This table reports the relationship between VC-backing, investor attention around a firm's IPO (as proxied by pre-IPO media coverage), and the absolute value of the offer price revision. *Ln(PR)* is the natural log of one plus the absolute value of the percentage difference between the IPO offer price and the midpoint of original filing range. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Ln(PR)	Ln(PR)	Ln(PR)	Ln(PR)	Ln(PR)
VC-Backing	0.014**			0.004	0.005
	(0.006)			(0.006)	(0.006)
Ln(Headlines)		0.014***			
		(0.002)			
Ln(Articles)			0.017***		
			(0.003)		
VC-Backing × High Headlines				0.022***	
				(0.007)	
High Headlines				0.013**	
				(0.006)	
VC-Backing × High Articles					0.022**
					(0.010)
High Articles					0.020***
					(0.007)
CM Rank	0.011***	0.011***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Asset)	-0.002	-0.003	-0.003*	-0.001	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fraction Sold	-0.022	-0.022	-0.023	-0.020	-0.018
	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)
Observations	3,591	3,591	3,591	3,591	3,591
Adjusted R-squared	0.102	0.107	0.112	0.109	0.104
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes

Table 5: Univariate Comparisons of Secondary Market and IPO Valuations

This table reports the distribution of immediate secondary market and IPO valuations of our sample firms going public from 1980 to 2009. Panels A, B, and C present the medians of secondary market valuations at the close of the first trading day relative to an industry peer (RVS_0), which are computed based on market price-to-sales, market price-to-EBITDA, and market price-to-earnings multiple, respectively. Panels D, E, and F present the medians of IPO firm valuations relative to an industry peer (*RVO*), which are computed based on market price-to-sales, market price-to-EBITDA, and market price-to-earnings multiple, respectively. The industry peer is a comparable publicly traded firm generated by the comparable firm approach. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively, for the differences in medians of valuations between VC-backed and non-VC-backed firms.

	VC-Backed IPOs		Non-VC-Backed IPOs		Test of Differences	
Year	No. of Issues	Median	No. of Issues	Median	Difference	p-value
Panel A: RVS_0 Based on Price/Sales Multiple						
1980-1989	270	2.289	441	1.553	0.736***	0.003
1990-1999	845	2.748	968	1.534	1.214***	0.000
2000-2009	327	2.614	249	1.152	1.462***	0.000
Whole Sample	1442	2.625	1658	1.488	1.137***	0.000
Panel B: RVS_0 Based on Price/EBITDA Multiple						
1980-1989	209	1.783	393	1.347	0.436***	0.005
1990-1999	520	2.158	807	1.311	0.847***	0.000
2000-2009	130	2.099	212	0.947	1.152***	0.000
Whole Sample	859	2.022	1412	1.282	0.740***	0.000
Panel C: RVS_0 Based on Price/Earnings Multiple						
1980-1989	196	1.581	333	1.174	0.407***	0.001
1990-1999	398	1.725	611	1.354	0.371***	0.002
2000-2009	87	1.933	143	1.354	0.579**	0.041
Whole Sample	681	1.686	1087	1.267	0.419***	0.000
Panel D: RVO Based on Price/Sales Multiple						
1980-1989	270	2.182	441	1.398	0.783***	0.000
1990-1999	845	2.352	968	1.362	0.990***	0.000
2000-2009	327	2.294	249	1.041	1.253***	0.000
Whole Sample	1442	2.297	1658	1.345	0.952***	0.000
Panel E: RVO Based on Price/EBITDA Multiple						
1980-1989	209	1.649	393	1.232	0.417***	0.004
1990-1999	520	1.802	807	1.188	0.614***	0.000
2000-2009	130	1.697	212	0.877	0.820***	0.000
Whole Sample	859	1.761	1412	1.148	0.613***	0.000
Panel F: RVO Based on Price/Earnings Multiple						
1980-1989	196	1.455	333	1.091	0.364***	0.007
1990-1999	398	1.420	611	1.185	0.234***	0.006
2000-2009	87	1.465	143	1.179	0.286*	0.077
Whole Sample	681	1.436	1087	1.145	0.291***	0.000

Table 6: VC-Backing, Investor Attention, and Secondary Market Valuations

This table reports the relationship of VC-backing, investor attention around a firm's IPO (as proxied by pre-IPO media coverage), and the valuation of an IPO firm in the immediate post-IPO secondary market. *Ln(RVS$_0$)* is the natural log of the valuation of an IPO firm at the close of the first trading day in the secondary market relative to an industry peer. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Ln(RVS$_0$)	Ln(RVS$_0$)	Ln(RVS$_0$)	Ln(RVS$_0$)	Ln(RVS$_0$)
VC-Backing	0.369***			0.242***	0.309***
	(0.050)			(0.055)	(0.062)
Ln(Headlines)		0.115***			
		(0.031)			
Ln(Articles)			0.085***		
			(0.029)		
VC-Backing × High Headlines				0.285***	
				(0.090)	
High Headlines				0.043	
				(0.061)	
VC-Backing × High Articles					0.181**
					(0.078)
High Articles					0.099
					(0.079)
CM Rank	0.090***	0.109***	0.109***	0.084***	0.100***
	(0.017)	(0.018)	(0.018)	(0.017)	(0.015)
Ln(Asset)	-0.237***	-0.267***	-0.271***	-0.233***	-0.259***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.030)
Fraction Sold	-1.212***	-1.266***	-1.274***	-1.196***	-1.230***
	(0.422)	(0.450)	(0.457)	(0.406)	(0.417)
Observations	2,890	2,890	2,890	2,890	2,890
Adjusted R-squared	0.223	0.214	0.213	0.228	0.221
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes

Table 7: VC-Backing, Investor Attention, and IPO Valuations

This table reports the relationship of VC-backing, investor attention around a firm's IPO (as proxied by pre-IPO media coverage), and IPO valuation. *Ln(RVO)* is the natural log of the valuation of an IPO firm at offer relative to an industry peer. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Ln(RVO)	Ln(RVO)	Ln(RVO)	Ln(RVO)	Ln(RVO)
VC-Backing	0.325***			0.236***	0.307***
	(0.048)			(0.054)	(0.059)
Ln(Headlines)		0.095***			
		(0.028)			
Ln(Articles)			0.068**		
			(0.027)		
VC-Backing × High Headlines				0.194**	
				(0.084)	
High Headlines				0.070	
				(0.058)	
VC-Backing × High Articles					0.083
					(0.078)
High Articles					0.128
					(0.081)
CM Rank	0.089***	0.106***	0.106***	0.084***	0.100***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)
Ln(Asset)	-0.251***	-0.277***	-0.280***	-0.249***	-0.271***
	(0.034)	(0.034)	(0.034)	(0.033)	(0.027)
Fraction Sold	-1.128***	-1.177***	-1.184***	-1.117***	-1.145***
	(0.380)	(0.404)	(0.410)	(0.367)	(0.379)
Observations	2,890	2,890	2,890	2,890	2,890
Adjusted R-squared	0.184	0.176	0.175	0.188	0.182
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes

Table 8: VC-Backing, Investor Attention, and IPO Initial Returns

This table reports the relationship between VC-backing, investor attention around a firm's IPO (as proxied by pre-IPO media coverage), and IPO initial returns. *Initial Ret* is the percentage change from the offer price to the first-day closing price in the secondary market. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Initial Ret	Initial Ret	Initial Ret	Initial Ret	Initial Ret
VC-Backing	0.045***			-0.000	-0.014
	(0.010)			(0.011)	(0.013)
Ln(Headlines)		0.034***			
		(0.010)			
Ln(Articles)			0.031***		
			(0.009)		
VC-Backing × High Headlines				0.105***	
				(0.029)	
High Headlines				-0.023	
				(0.017)	
VC-Backing × High Articles					0.122***
					(0.037)
High Articles					-0.039*
					(0.021)
CM Rank	0.017**	0.017**	0.016**	0.015*	0.016**
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Ln(Asset)	-0.022***	-0.024***	-0.026***	-0.019***	-0.020***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Fraction Sold	-0.166**	-0.170**	-0.172**	-0.161**	-0.157**
	(0.078)	(0.078)	(0.080)	(0.075)	(0.075)
Observations	3,696	3,696	3,696	3,696	3,696
Adjusted R-squared	0.233	0.235	0.235	0.237	0.238
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes

Table 9: VC Reputation, Investor Attention, and IPO Characteristics

This table reports the relationship between VC reputation, investor attention, and IPO characteristics including secondary market and IPO valuations as well as IPO initial returns. *Ln(PR)* is the natural log of one plus the absolute value of the percentage difference between the IPO offer price and the midpoint of original filing range. *Ln(RVS_0)* is the natural log of the valuation of an IPO firm at the close of the first trading day in the secondary market relative to an industry peer. *Ln(RVO)* is the natural log of the valuation of an IPO firm at offer relative to an industry peer. *Initial Ret* is the percentage change from the offer price to the first-day closing price in the secondary market. *High-Rep-VC-Backing* is a dummy variable equal to 1 if the average market share of funds raised by the IPO firm's lead VC investors is above the 75th percentile of the sample and 0 otherwise. *Low-Rep-VC-Backing* is dummy variable equal to 1 if the average market share of funds raised by the IPO firm's lead VC investors is equal to or below the 75th percentile of the sample and 0 otherwise. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the industry level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Ln(RVS_0)	Ln(RVS_0)	Ln(RVS_0)	Ln(RVO)	Ln(RVO)	Ln(RVO)	Initial Ret	Initial Ret	Initial Ret
High-Rep-VC-Backing × High Headlines		0.478***			0.338***			0.197***	
		(0.087)			(0.088)			(0.052)	
Low-Rep-VC-Backing × High Headlines		0.229**			0.154			0.075***	
		(0.107)			(0.101)			(0.023)	
High-Rep-VC-Backing × High Articles			0.276**			0.140			0.210***
			(0.106)			(0.093)			(0.056)
Low-Rep-VC-Backing × High Articles			0.131			0.051			0.096***
			(0.091)			(0.092)			(0.033)
High-Rep-VC-Backing	0.371***	0.122	0.214**	0.314***	0.133	0.226**	0.069***	-0.030*	-0.044*
	(0.098)	(0.088)	(0.102)	(0.089)	(0.084)	(0.096)	(0.019)	(0.018)	(0.023)
Low-Rep-VC-Backing	0.367***	0.273***	0.303***	0.328***	0.263***	0.301***	0.037***	0.008	-0.006
	(0.051)	(0.060)	(0.060)	(0.049)	(0.061)	(0.057)	(0.008)	(0.010)	(0.014)
High Headline		0.042			0.069			-0.023	
		(0.060)			(0.057)			(0.016)	
High Article			0.092			0.119			-0.041*
			(0.079)			(0.080)			(0.021)
CM Rank	0.091***	0.084***	0.086***	0.089***	0.084***	0.086***	0.017**	0.015*	0.016**
	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.008)	(0.008)	(0.008)
Ln(Assets)	-0.238***	-0.235***	-0.240***	-0.252***	-0.251***	-0.256***	-0.022***	-0.020***	-0.020***
	(0.038)	(0.038)	(0.038)	(0.033)	(0.033)	(0.033)	(0.004)	(0.004)	(0.004)
Fraction Sold	-1.213***	-1.193***	-1.199***	-1.130***	-1.115***	-1.122***	-0.166**	-0.159**	-0.155**
	(0.423)	(0.406)	(0.416)	(0.380)	(0.368)	(0.378)	(0.078)	(0.075)	(0.074)
Observations	2,890	2,890	2,890	2,890	2,890	2,890	3,696	3,696	3,696
Adjusted R-squared	0.223	0.229	0.225	0.184	0.188	0.185	0.234	0.238	0.239
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
High-Rep-VC-Backing – Low-Rep-VC-Backing	0.004			-0.014			0.032**		
High-Rep-VC-Backing × High Headlines – Low-Rep-VC-Backing × High Headlines		0.249**			0.184*			0.122***	
High-Rep-VC-Backing × High Articles – Low-Rep-VC-Backing × High Articles			0.145			0.089			0.114**

Table 10: VC-Backing, Investor Attention, and Institutional Investor Participation

This table reports the relationship between VC-backing, investor attention around a firm's IPO (as proxied by pre-IPO media coverage), and the number of institutional investors holding the IPO firm's equity. *Ln(N_Inst)* is the natural log of the number of institutional investors that hold the stocks of the firm at the end of the first fiscal year after IPO. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to the IPO date. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Ln(N_Inst)	Ln(N_Inst)	Ln(N_Inst)	Ln(N_Inst)	Ln(N_Inst)
VC-Backing	0.212***			0.174***	0.213***
	(0.034)			(0.037)	(0.037)
Ln(Headlines)		0.066***			
		(0.012)			
Ln(Articles)			0.075***		
			(0.015)		
VC-Backing × High Headlines				0.080*	
				(0.042)	
High Headlines				0.028	
				(0.049)	
VC-Backing × High Articles					-0.009
					(0.054)
High Articles					0.086*
					(0.048)
CM Rank	0.171***	0.180***	0.177***	0.168***	0.169***
	(0.013)	(0.015)	(0.016)	(0.013)	(0.013)
Ln(Asset)	0.177***	0.166***	0.162***	0.179***	0.175***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
Fraction Sold	-0.171**	-0.205**	-0.208**	-0.166**	-0.171**
	(0.076)	(0.090)	(0.092)	(0.073)	(0.074)
Observations	3,538	3,538	3,538	3,538	3,538
Adjusted R-squared	0.585	0.581	0.582	0.585	0.585
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes

Table 11: VC-Backing, Investor Attention, and Financial Analyst Coverage

This table reports the relationship between VC-backing, investor attention around a firm's IPO (as proxied by pre-IPO media coverage), and the number of financial analysts that follow the firm after IPO. *Ln(N_An)* is the natural log of the number of analysts providing earnings forecast at the end of the first fiscal year after IPO. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(Headlines)* is the natural log of one plus the number of headlines that have mentioned the IPO firm in the two months prior to the IPO date. *Ln(Articles)* is the natural log of one plus the number of articles that have mentioned the IPO firm in the two months prior to IPO. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
VARIABLES	Ln(N_An)	Ln(N_An)	Ln(N_An)	Ln(N_An)	Ln(N_An)
VC-Backing	0.136***			0.110***	0.110***
	(0.016)			(0.022)	(0.027)
Ln(Headlines)		0.034***			
		(0.007)			
Ln(Articles)			0.049***		
			(0.012)		
VC-Backing × High Headlines				0.055*	
				(0.031)	
High Headlines				-0.000	
				(0.022)	
VC-Backing × High Articles					0.048
					(0.034)
High Articles					0.002
					(0.028)
CM Rank	0.080***	0.087***	0.084***	0.079***	0.079***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Ln(Asset)	0.073***	0.064***	0.062***	0.074***	0.073***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Fraction Sold	-0.093	-0.114*	-0.115*	-0.090	-0.090
	(0.182)	(0.186)	(0.179)	(0.185)	(0.177)
Observations	3,180	3,180	3,180	3,180	3,180
Adjusted R-squared	0.282	0.274	0.278	0.282	0.282
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes

Table 12: Univariate Comparisons of Secondary Market Valuations for VC-Backed and Non-VC-Backed IPO Firms over Time

This table presents the secondary market valuations of VC-backed and non-VC-backed IPO firms over time. Panels A, B, and C present the medians of secondary market valuations of IPO firms from the close of the first trading day in the secondary market up to three years after IPO, which are computed based on market price-to-sales, market price-to-EBITDA, and market price-to-earnings multiple of an industry peer, respectively. The industry peer is a comparable publicly traded firm generated by the comparable firm approach. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively, for the differences in median valuations between VC-backed and non-VC-backed subsamples.

	VC-Backed IPOs		Non-VC-Backed IPOs		Test of Differences	
Number of Years after IPO	No. of Issues	Median	No. of Issues	Median	Difference	p-value
Panel A: RVS_t based on Price/Sales Multiple						
0	1442	2.625	1658	1.488	1.137***	0.000
1	1261	1.821	1556	1.182	0.640***	0.000
2	1157	1.590	1345	1.015	0.575***	0.000
3	997	1.305	1136	1.062	0.243***	0.000
Panel B: RVS_t based on Price/EBITDA Multiple						
0	859	2.022	1412	1.282	0.740***	0.000
1	738	1.704	1233	1.128	0.576***	0.000
2	665	1.601	1036	1.027	0.574***	0.000
3	576	1.470	898	1.047	0.424***	0.000
Panel C: RVS_t based on Price/Earnings Multiple						
0	681	1.686	1087	1.267	0.419***	0.000
1	588	1.487	964	1.093	0.394***	0.000
2	480	1.373	764	1.068	0.306***	0.000
3	411	1.301	613	1.142	0.158**	0.035

Table 13: The Dynamics of Secondary Market Valuations over Time

Panel A reports the relationship between VC-backing, investor attention around a firm's IPO (as proxied by pre-IPO media coverage), and the secondary market valuations of IPO firms from the close of the first trading day in the secondary market up to three years after IPO. Panel B reports the relationship between high- and low-reputation VC-backing, investor attention, and the secondary market valuations over time. *Ln(RVS$_t$)* is the natural log of the relative valuation of an IPO firm in the secondary market in the *t*-th year after IPO, where *t* equals 0, 1, 2, and 3, and year 0 means at the close of the first trading day in the secondary market. *Time Trend* is a linear trend, defined as the number of years after IPO. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *High-Rep-VC-Backing* is a dummy variable equal to 1 if the average market share of funds raised by the IPO firm's lead VC investors is above the 75th percentile of the sample and 0 otherwise. *Low-Rep-VC-Backing* is dummy variable equal to 1 if the average market share of funds raised by the IPO firm's lead VC investors is equal to or below the 75th percentile of the sample and 0 otherwise. *High Headlines* is a dummy variable equal to 1 if the number of headlines that have mentioned the IPO firm is above the sample median and 0 otherwise. *High Articles* is a dummy variable equal to 1 if the number of articles that have mentioned the IPO firm is above the sample median and 0 otherwise. Constant, firm fixed effects, and calendar year fixed effects are included in all regressions. All standard errors are adjusted for clustering 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: VC-Backing, Investor Attention, and the Dynamics of Secondary Market Valuations over Time				
	(1)	(2)	(3)	(4)
VARIABLES	Ln(RVS_t)	Ln(RVS_t)	Ln(RVS_t)	Ln(RVS_t)
Time Trend	-0.152***	-0.106***	-0.104***	-0.114***
	(0.023)	(0.019)	(0.021)	(0.020)
Time Trend × VC-Backing		-0.097***	-0.085***	-0.060**
		(0.024)	(0.029)	(0.028)
Time Trend × VC-Backing × High Headlines			-0.024	
			(0.045)	
Time Trend × High Headlines			-0.005	
			(0.022)	
Time Trend × VC-Backing × High Articles				-0.077*
				(0.042)
Time Trend × High Articles				0.019
				(0.032)
Observations	10,496	10,496	10,496	10,496
Adjusted R-squared	0.071	0.074	0.074	0.074
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: High- and Low-Reputation VC-Backing, Investor Attention, and the Dynamics of Secondary Market Valuations over Time			
	(1)	(2)	(3)
VARIABLES	Ln(RVS_t)	Ln(RVS_t)	Ln(RVS_t)
Time Trend	-0.107***	-0.106***	-0.113***
	(0.020)	(0.021)	(0.020)
Time Trend × High-Rep-VC-Backing	-0.103***	-0.041	-0.068**
	(0.026)	(0.030)	(0.027)
Time Trend × Low-Rep-VC-Backing	-0.091***	-0.093***	-0.060*
	(0.024)	(0.029)	(0.031)
Time Trend × High Headlines × High-Rep-VC-Backing		-0.122***	
		(0.040)	
Time Trend × High Headlines × Low-Rep-VC-Backing		0.003	
		(0.047)	
Time Trend × High Headlines		-0.004	
		(0.023)	
Time Trend × High Articles × High-Rep-VC-Backing			-0.070*
			(0.035)
Time Trend × High Articles × Low-Rep-VC-Backing			-0.067
			(0.050)
Time Trend × High Articles			0.016
			(0.032)
Observations	10,496	10,496	10,496
Adjusted R-squared	0.074	0.074	0.074
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Time Trend × High-Rep-VC-Backing – Time Trend × Low-Rep-VC-Backing	-0.012		
Time Trend × High Headlines × High-Rep-VC-Backing – Time Trend × High Headlines × Low-Rep-VC-Backing		-0.125***	
Time Trend × High Articles × High-Rep-VC-Backing – Time Trend × High Articles × Low-Rep-VC-Backing			-0.003

Table 14: Instrumental Variable Analysis of the Effect of VC-Backing on IPO Characteristics

This table reports the second-stage results of the Instrumental Variable regressions for the effect of VC-backing on various IPO characteristics. The instrumental variable used here is *LP Returns*, which is defined in Section 2.5.2. *VC-Backing* is a dummy variable equal to 1 if the firm is venture capitalist backed and 0 otherwise. *Ln(PR)* is the natural log of one plus the absolute value of the percentage difference between the IPO offer price and the midpoint of original filing range. *Ln(RVS_0)* is the natural log of the valuation of an IPO firm at the close of the first trading day in the secondary market relative to an industry peer. *Ln(RVO)* is the natural log of the valuation of an IPO firm at offer relative to an industry peer. *Initial Ret* is the percentage change from the offer price to the first-day closing price in the secondary market. *Ln(N_Inst)* is the natural log of the number of institutions that hold the stocks of the firm at the end of the first fiscal year after IPO. *Ln(N_An)* is the natural log of the number of analysts providing earnings forecast at the end of the first fiscal year after IPO. *CM Rank* is the Carter-Manaster rank of the lead underwriter for the IPO firm. *Ln(Asset)* is the natural log of the firm's pre-IPO assets. *Fraction Sold* is the fraction of firm equity sold in the IPO. Constant, industry fixed effects based on Fama French 48 industry classifications, IPO year fixed effects, and stock exchange fixed effects are included in all regressions. All standard errors are adjusted for clustering at the 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)
	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
VARIABLES	Ln(PR)	Ln(RVS_0)	Ln(RVO)	Initial Ret	Ln(N_Inst)	Ln(N_An)
VC-Backing	0.079**	0.785***	1.295***	0.566***	0.995***	0.454***
	(0.032)	(0.229)	(0.337)	(0.082)	(0.269)	(0.157)
CM Rank	0.006**	0.004	0.020	-0.016**	0.121***	0.059***
	(0.003)	(0.017)	(0.029)	(0.007)	(0.025)	(0.014)
Ln(Asset)	0.001	-0.173***	-0.183***	0.004	0.216***	0.088***
	(0.002)	(0.015)	(0.042)	(0.005)	(0.023)	(0.013)
Fraction Sold	-0.005	-0.901***	-0.920***	-0.065*	-0.032	-0.038
	(0.015)	(0.228)	(0.289)	(0.034)	(0.094)	(0.057)
Observations	3,258	3,140	2,571	3,331	3,204	2,951
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Exchange FE	Yes	Yes	Yes	Yes	Yes	Yes

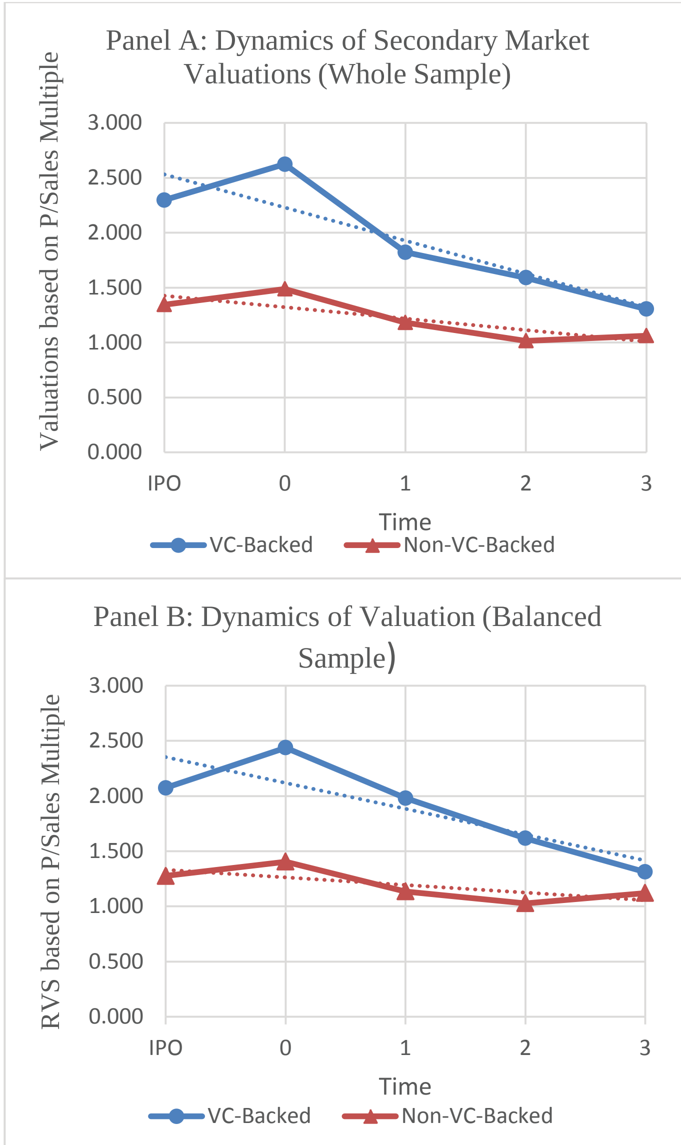

Figure 2: Valuations of VC-Backed and Non-VC-Backed IPOs over Time

This figure depicts the median firm valuations of VC-backed and non-VC-backed firm IPOs over time from the IPO date up to three years after the first trading day in the secondary market. On the horizontal axis, time *IPO* is the firm's IPO date. Time *0* is the close of the first trading day in the secondary market, while times *1* through *3* correspond to exactly one, two, and three years after the first trading day in the secondary market.

3 Top Management Human Capital, Inventor Mobility, and Corporate Innovation

3.1 Introduction

The effectiveness of a firm's top management team in investing and managing innovative projects may determine the long-term success of the firm. Indeed, prior literature suggests that firms' investments in research and development (R&D) and their innovative output (measured by patents and citations) may have a positive impact on the long-term financial health of the firm. Given this, there is surprisingly little analysis into how the human capital or "quality" of the top management team of a firm may impact the firm's innovative output. We aim to fill this gap in the literature.

One strand of theoretical literature suggests that higher quality management teams may invest in long-run value enhancing projects (e.g., Chemmanur and Jiao (2012)). Given that innovative projects are among such long-run value enhancing projects (e.g., Hirshleifer, Hsu, and Li (2013) and Griliches (1990)), we expect that higher quality management teams will invest in more innovative projects and will have a greater extent of innovative output, on average. Further, they can accomplish this by having better foresight into the potential value of innovative investment opportunities and by more effectively managing innovative resources such as physical assets (research equipment) and human capital (scientists and inventors). For instance, they may provide an environment that fosters greater failure tolerance in the sense of Manso (2011).[66] Given this, firms with higher quality management teams may attract inventors with greater skills to work for them.

The above arguments lead to several testable predictions. First, firms with higher

[66] An example of this is Google's high-risk R&D venture called Google X. Media articles suggest that "......Google X is the search giant's factory for moonshots, those million-to-one scientific bets that require generous amounts of capital, massive leaps of faith, and a willingness to break things." See, *Inside Google's Secret Labs*, Bloomberg Businessweek, May 22, 2013.

quality top management teams will invest more in R&D. Second, firms with higher quality management teams will have a greater extent of innovation productivity (measured by the number of patents) and higher quality innovation (measured by total citations and citations per patent). Third, better management of innovative assets by higher quality management teams will be reflected in a higher extent of innovative efficiency (e.g., patents per R&D dollar) for such firms. Fourth, the effect of management team quality on innovative output will be stronger for firms facing financial constraints and for firms in competitive industries. Since such firms are at a disadvantage relative to other firms, the "leg-up" provided by a higher quality top management team will enhance their future prospects more. Finally, firms with higher quality management teams will have a larger net inflow of inventors (controlling for R&D expenditures) and will hire higher quality inventors (as measured by their prior track record of citations per patent).

An empirical analysis of the relationship between management quality and innovation faces two challenges. First, measuring the human capital of a firm's top management team (which we refer to as management quality) involves subjective notions of what constitutes a higher quality management team. Second, potential endogeneity can confound empirical findings on the relation between management quality and innovation. In particular, there may be endogenous matching between higher quality management teams and higher quality firms. We overcome the first challenge by creating a management team quality index from various measures used previously in the literature, such as management team size, fraction of managers with MBAs, the average employment- and education-based connections of each manager in the management team, the fraction of members with prior work experience in the top management team, the average number of prior board positions that each manager serves on, and the fraction of managers with PhDs. These measures are adjusted for firm size. We create our index of management quality using common factor analysis of the above-mentioned measures of top management quality and extracting a single "management quality factor."[67]

We overcome the second challenge related to endogeneity by using an instrumental variable (IV) analysis. Our instrument is motivated by the following facts. First, potential managers available for hire by a firm often come from established firms in the same industry and may leave such firms as a result of acquisitions. In other words, there is a strong correlation between the movement of managers across firms and the number of acquisitions in the industry the firm belongs to. Second, the enforceability of non-compete clauses, which are commonly used in the employment contracts for top management teams to prohibit them from joining or founding a rival company within one or two years of leaving, affects the mobility of managers across firms. Motivated by the above facts, we instrument for top management quality (as measured by our management quality factor) using a plausibly exogenous shock to the supply of top executives available for hire by a firm, namely, the number of acquisitions in the firm's industry five years prior weighted by the an index measuring the enforceability of non-compete clauses.

We analyze the relationship between management quality and firm performance using a panel data set of 4,389 firms covering the period 1999 to 2009. We obtain the biographical data on the top managers of firms from the BoardEx database, patent and citation information from the patent data set created by Kogan, Papanikolaou, Seru, and Stoffman (2012) based on data from the United States Patent and Trademark Office (USPTO), and inventor information associated with each patent from the U.S. Patent Inventor Database (1975-

[67]Starting with the pioneering work of Becker (1964) and Ben-Porath (1967), the labor economics literature has focused on the human capital of workers. The Becker view is that human capital increases a worker's productivity in all tasks, though possibly differentially in different tasks, organizations, and situations. In the Becker view, although the role of human capital in the production process may be quite complex, we can think of it as representable by a unidimensional measure, such as a worker's stock of knowledge or skills, and this stock is directly part of the production function. When analyzing the human capital of the members of a firm's top management team, our view is that managerial human capital is multidimensional, consisting of many different aspects which we capture using the individual measures we mention here, and collapse into one factor, making use of common factor analysis. Thus, our view of human capital is closer to the view of the social psychologist Howard Gardner (see, e.g., Gardner (1983), and Acemoglu and Autor (2011) for a review). An advantage of such a multidimensional approach is that we are able to capture differences in not only the quantity but also the quality of the human capital of the top management teams across firms. See, e.g., Chemmanur and Paeglis (2005) or Chemmanur, Paeglis, and Simonyan (2011), who make use of such a multidimensional approach in their measurement of top management human capital (in other contexts).

2010): see Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014) for a detailed description of the latter database.

Our empirical results can be summarized as follows. First, we find that higher quality management teams invest more in R&D expenditures, showing that they devote a larger amount of resources (input) toward innovative activities. Second, firms with higher quality management teams have a greater extent of innovation output (measured by the number of patents) and higher quality innovation output (measured by total citations and citations per patent). Further, these effects are economically significant. For instance, a one inter-quartile range increase in management quality increases firm patents by 12.8%. We find similar results when we use individual proxies for management quality (such as team size, education, connections, etc.) rather than our overall management quality factor. Third, we find that firms with higher quality management teams produce more patents and citations per R&D dollar, that is, have greater innovative efficiency (see, e.g., Hershleifer, Hsu, and Li (2013)). All the above results on the relation between management quality and corporate innovation are confirmed by our IV analysis making use of the instrument discussed above, thus indicating that management quality has a positive and causal effect on corporate innovation. Finally, the relation between top management team quality and innovation is stronger for firms in financially constrained industries and for firms in more competitive industries.

We then investigate the mechanisms through which higher quality management teams may foster greater innovation in their firms. We argue that higher quality management teams may provide more resources to R&D, manage R&D resources better, and provide a more failure tolerant climate for inventors to succeed in. This, in turn, may make firms with higher management quality attractive to higher quality inventors. Thus, one way that higher quality top management teams may enhance innovation is by hiring more and higher quality inventors to work for the firm. Our fifth result is consistent with this conjecture: we find that firms with higher quality management teams experience greater net inflows of inventors (controlling for R&D expenditures), particularly of higher quality inventors. Inventors are defined to be of higher quality if their record of past citations per patent is above that of the median inventor in our sample. We also find that the average citations per patent of incoming inventors into firms with higher quality management teams is higher than the average citations per patent of outgoing inventors from such firms.

Finally, we examine the nature of innovative strategies undertaken by firms with higher quality management teams. In particular, we analyze whether firms with higher quality management teams engage more in exploratory innovative strategies (where they venture into the development of newer technologies or pursue innovations in areas that are less familiar to the firm) or in exploitative innovative strategies (where they may pursue innovations using more conventional technologies or in areas that are more familiar to the firm). To analyze this, we divide the patents obtained by firms into three categories based on whether their citations fall into the group of patents receiving the highest number (top ten percent) of citations ("highly successful innovations"); no citations at all ("unsuccessful innovations"); or somewhere in between ("moderately successful innovations"). If higher management quality firms are engaged in "exploratory" strategies, which are more risky, we would expect such firms to be associated with a larger number of highly successful and a larger number of quite unsuccessful innovations compared to lower management quality firms. Alternatively, if higher management quality firms are engaged in "exploitative" innovative strategies, we would expect such firms to be associated with more moderately successful innovations compared to those achieved by lower management quality firms. The evidence indicates that higher quality management team firms pursue both exploratory and exploitative strategies: we find that firms with higher quality management teams have a larger number of successful innovations, unsuccessful innovations, and moderately successful innovations. However, the successful innovations increase to a greater extent with top management quality compared to unsuccessful and moderately successful innovations.

We contribute to two strands in the literature. First, we contribute to the recent literature that has analyzed the determinants of innovation in firms theoretically as well as empirically (e.g., Manso (2011) and Marx, Strumsky, and Fleming (2009)) and their impact on firm performance (e.g., Hirshleifer, Hsu, and Li (2013); Gu (2005); Eberhart, Maxwell, and Siddique (2004); Lanjouw and Schankerman (2004); Lerner (1994); and Griliches (1990)). Much of the existing literature has focused on firm characteristics other than management quality and their effects on innovation. Some of these characteristics are: managerial compensation (e.g., Lerner and Wulf (2007); Ederer and Manso (2013)); firms' going public decisions (e.g., Bernstein (2015)); private equity or venture capital involvement (e.g., Lerner, Sorensen, and Strömberg (2011); Tian and Wang (2014); Chemmanur, Loutskina, and Tian (2014)); anti-takeover provisions (e.g., Atanassov (2013); Chemmanur and Tian (2014); Sapra, Subramanian, and Subramanian (2014)); institutional ownership (e.g., Aghion, Van Reenen, and Zingales (2013)); and conglomerate structure (e.g., Seru (2014)). In a contemporaneous paper, Custodio, Ferreira, and Matos (2015) analyzes how the general versus firm-specific human capital of CEOs affects corporate innovation. Ours is, however, the first paper in the literature to analyze the relation between top management team quality and corporate innovation, thus moving the literature in a new direction.

Second, we contribute to the literature linking management quality and talent to firm performance, investments, and financing. For instance, Bertrand and Schoar (2003) study the effect of top managers on a firm's financial and investment policies. They find that manager fixed effects explain some of the heterogeneity in the investment, financial, and organizational practices of firms. Ewens and Rhodes-Kropf (2015) use a similar fixed-effects methodology to investigate whether individual venture capitalists have repeatable investment skill and the extent to which their skill is impacted by the venture capital firm where they work. They accomplish this by tracking the performance of individual venture capitalists' investments over time as they move between firms. Chemmanur, Kong, and Krishnan (2015) relate management quality measures similar to ours to firm stock performance, operating performance, and valuation. They also find that higher quality management teams invest more in R&D expenditures. Unlike them, however, we focus on measures of innovative output, innovative efficiency, and inventor mobility. Further, we add to the above literature by analyzing the mechanisms through which higher quality management teams may increase innovation and by analyzing the nature of the innovative strategies adopted by firms with higher versus lower top management team quality.[68,69,70] We provide evidence suggesting that higher quality managers may enhance innovation by attracting higher quality inventors to work for their firm. Our evidence also suggests that higher quality managers are not simply "buying" innovation through greater R&D expenditures, but obtain a higher extent of innovative output per R&D dollar (higher "bang for the R&D buck"). Finally, we demonstrate a causal relation between management quality and innovation.

Two important papers in the economics literature that have implications for our paper are Sah and Stiglitz (1986, 1991). Their theoretical analysis implies that larger management teams are more likely to reject bad projects, since a project will be accepted only if several group members agree that it is good. One of the implications of their theory is that performance should be less variable when a greater number of executives have influence over

[68]Our paper is also related to Chemmanur and Paeglis (2005) and Chemmanur, Paeglis, and Simonyan (2009). These papers also make use of a management quality factor based on common factor analysis on some individual proxies of management quality to study the relationship between management quality and IPO characteristics (in the case of the former paper) and SEO characteristics and firm financial policies around the SEO (in the case of the latter paper). In contrast to Chemmanur and Paeglis (2005), who study firms going public, our focus in the current paper is on larger, more established firms and how management quality relates to innovative output, innovative efficiency, and inventor mobility. Further, while the above two papers make use of cross-sectional data hand-collected from IPO and SEO prospectuses respectively, our paper makes use of a large panel data set that allows us to capture the time series variation in management quality as well.

[69]In more distantly related research, Bloom and Van Reenen (2007) use an innovative survey tool to collect management practices data from various countries and show that measures of managerial practice are strongly associated with firm-level productivity, profitability, Tobin's Q, and survival rates. See also Bloom, Eifert, Mahajan, McKenzie, and Roberts (2012), who ran a management field experiment on large textile firms in India, and show that adopting better management practices raised productivity by 17% on average in the first year after the adoption of these practices. Unlike these papers, which study the effects of management practices using self-reported survey data, we are able to use publicly available data on the characteristics of top management teams of firms to study the effect of the human capital of top firm management on innovation.

[70]Our paper also indirectly related to the literature on the determinants of CEO quality and how it affects firm performance (see, e.g., Adams, Almeida, and Ferreira (2005) and Malmendier and Tate (2005)). See also Kaplan, Klebanov, and Sorensen (2012), who study the individual characteristics of CEO candidates for companies involved in buyout and venture capital transactions and relate them to the subsequent performance of their companies.

corporate decisions.[71] Finally, our paper is also related to the growing literature in organizational economics linking the importance of agents across and within organizations. For example, Bandiera, Barankay, and Rasul (2010) find that workers are more productive when they work with higher ability co-workers and less productive when they work with lower ability co-workers (see also Bandiera, Barankay, and Rasul (2005)).[72]

The rest of the paper is organized as follows. Section 3.2 discusses the underlying theory and develops testable hypotheses. Section 3.3 outlines the data and the sample selection procedure. Section 3.4 provides a discussion of our empirical results relating our measure of management quality to innovation and innovative efficiency. Section 3.5 investigates possible underlying mechanisms. Section 3.6 presents a discussion of our robustness test results. Section 3.7 concludes.

3.2 Theory and Hypothesis Development

In this section, we briefly discuss the underlying theory and develop hypotheses for our empirical tests. Our theoretical motivation partially follows Chemmanur and Jiao (2012), who study a setting in which managers with greater talent or ability are able to create greater long-run cash flows by undertaking long-term projects. However, since their talent is private information, and, since short-term projects come to fruition earlier, myopia or short-termism induced by the stock market (for example, due to the possibility of rivals appearing and successfully taking over the firm in the absence of favorable signals of project success in the short run) impose pressures on them to undertake short-term rather than long-term projects (see also Stein (1988) for another model of corporate myopia). However, more capable managers also have an incentive to undertake long-term rather than short-term projects, since they are able to create greater long-term value by doing so. In such a setting, the equity market

[71] The organizational behavior literature on the effect of managerial discretion on firm performance is also indirectly related to our paper: see Finkelstein and Hambrick (1996) for a review.

[72] In a somewhat different context, Chevalier and Ellison (1999) study the relationship between the performance of mutual funds and the characteristics (age, experience, education, and Scholastic Aptitude Test (SAT) scores) of their fund managers. They find that managers who attended higher-SAT undergraduate institutions had significantly higher risk-adjusted excess returns.

prices the equity of firms undertaking long-term projects at a discount, since they are not able to fully observe true managerial ability; however, firms with managers having a higher perceived quality (i.e., with a greater reputation for ability) suffer only a smaller valuation discount if they undertake long-term projects. In summary, managers' choice between long-term and short-term projects is driven by the trade-off between the pressures induced by a myopic stock market versus the ability (and desire) of more able managers to create greater value in the long-run by undertaking long-term projects.[73] Given that innovative projects are long-term projects characterized by short-term failures and experimentation (that increases the gestation time of these projects), managers with greater perceived ability will undertake a greater proportion of long-term (innovative) projects.[74]

The above theoretical framework provides us with our first set of testable implications. First, top management teams with higher (perceived) quality are likely to devote a greater amount of resources to innovation activities. Thus, firms with higher quality management teams will be characterized by larger R&D expenditures, i.e., a larger input of their resources into innovation activities. This is the first hypothesis (**H1**) that we test here. Further, we would expect such firms to be characterized by greater innovation output and higher quality innovation output (after controlling for R&D expenditures). This is the second hypothesis (**H2**) that we test there. Such firms will also be characterized by greater innovative efficiency (i.e., greater innovation output and higher quality innovation output per dollar of R&D capital investment). This is the third hypothesis (**H3**) that we test here.

We also test whether the relationship between management quality and innovation pro-

[73]Formally, in Chemmanur and Jiao (2012), the objective function of the manager is a weighted average of the short-run and long-run stock price. Thus, while talented (higher ability) managers will suffer a discount in the firm's short-run stock valuation if they take a greater proportion of long-term projects (since their equity will be priced in a pooling equilibrium with firms with less talented managers), more talented managers have an incentive to undertake a greater proportion of long-term projects since these projects allow them to create greater long-run value and thereby a higher long-run stock price.

[74]Note that, while the true quality of firm management may be private information, the management quality as perceived by outsiders (captured by our management quality measures) affects managers' choice of the proportion of innovative (long-term) projects to undertake. This is because, for managers with higher perceived quality (i.e., with a greater reputation for being talented), the cost of undertaking long-term projects (arising from a firm valuation discount in the short run) will be smaller, leading them to undertake a larger proportion of long-term (innovative) projects.

ductivity is stronger in some industries than in others. First, consider firms in financially constrained industries. Given their financial constraints, such firms will have only a limited amount of resources to devote to innovation. If the relation between management quality and innovation is partly driven by more effective resource management on the part of higher management quality firms, we would expect the relationship between management quality and innovation to be stronger for firms in financially constrained industries (**H4**).[75] Next, consider firms in more competitive versus less competitive industries. Scientists and engineers (inventors) in more competitive industries are likely to have greater outside employment opportunities, so that the talented inventors are likely to be in limited supply in these industries. Therefore, since firms with higher quality management teams are able to attract a greater proportion of these talented inventors in limited supply, we would expect that the relationship between management quality and innovation productivity to be stronger in more competitive industries (**H5**).

We now analyze the channels through which firms with higher top management quality are able to generate greater innovation productivity (i.e., greater innovation output for a given amount of resources devoted to R&D expenditures). Consistent with our conjecture that higher quality management teams may be able to manage their innovative activities more efficiently, we hypothesize that firms with higher quality management teams are able to hire more inventors for a given amount of R&D expenditures (**H6**). We further conjecture that firms with higher quality management teams are likely to hire higher quality inventors, who are more innovative (as measured by their prior track record of citations per patent).[76]

[75]The idea here is that, while firms in financially unconstrained industries may be able to partially compensate for not having higher quality management teams by devoting more resources to innovative activities (for example, by buying higher quality equipment), firms in financially constrained industries will be less able to do so, so that the relationship between management quality and innovation will be stronger for the latter category of firms.

[76]For instance, one way in which firms with higher quality management teams may be able to attract higher quality inventors is by promoting a more failure tolerant work environment (in the sense of Manso (2011)). Manso (2011) has argued that an important variable in encouraging innovation is failure tolerance. While Manso (2011) does not distinguish between higher and lower quality firm management teams, if we add the additional assumption that higher quality managers are also more failure tolerant, then it will be the case that firms that have higher quality management teams will also have a more failure tolerant work environment (more conducive to innovative activities).

This is the next hypothesis that we test here (**H7**).

We now delve deeper into the possible differences in the innovation strategies adopted by firms with higher versus lower management quality. One possibility is that higher management quality firms engage in more exploratory innovation strategies (in the sense of Balsmeier, Fleming and Manso (2016)), so that they venture into the development of newer technologies or pursue innovation in areas less familiar to the firm. Given that such an exploratory strategy is more risky, under this scenario we would expect higher management quality firms to be associated with a larger number of highly successful and a larger number of quite unsuccessful innovations (as measured by citations per patent) compared to lower management quality firms: in other words, in this case higher management quality firms will have a larger number of patents in the two tails of the patent quality distribution (**H8A**). Alternatively, higher management quality firms may engage more in "exploitative" innovative strategies (also in the sense of Balsmeier, Fleming and Manso (2016)), implying that they pursue innovations using more conventional technologies or in areas that are more familiar to the firm. Under the latter scenario, we would expect firms with higher management quality to be associated with more moderately successful innovations (again measured by citations per patent) compared to those achieved by lower management quality firms (**H8B**).[77]

3.3 Data and Sample Selection

3.3.1 Sample Selection

Our sample is derived from multiple data sources. Our primary data source of the biographical information of senior managers is the BoardEx database. The BoardEx database contains data on college education, graduate education, past employment history (including beginning and ending dates of various roles), current employment status (including primary employment and outside roles), and social activities (including memberships, positions held

[77]It is difficult to predict from *a priori* theoretical considerations which of the above two scenarios will be realized in practice. We will therefore leave this question to be resolved empirically.

in various foundations and charitable groups, etc.). The main information we are making use of in this paper is education, employment history, and demographic information. We collect firm-year patent and citation information from the the patent data set created by Kogan, Papanikolaou, Seru, and Stoffman (2012) (henceforth KPSS). We collect the inventor information associated with each patent from the U.S. Patent Inventor Database (1975-2010) (see Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014)). To calculate control variables, we collect financial statement items from Compustat and stock price information from CRSP. To construct the instrumental variables as we described earlier, we collect information on mergers and acquisitions from the SDC Mergers & Acquisitions database.

The unique company-level identification code in BoardEx is "Company ID", which is unique to BoardEx and cannot be used to merge with other databases such as Compustat and CRSP. We link the BoardEx database to Compustat and CRSP in the following way. BoardEx provides CIK, the International Security Identification Number (ISIN), and the company name. The "Company ID" in BoardEx is matched with the PERMNO in CRSP by either CIK or CUSIP (which is derived from ISIN). After matching by CIK or CUSIP, we check the accuracy of the matches by comparing the company name from BoardEx with company names from CRSP and Compustat.

The KPSS patent data set provides detailed data for all patents that are granted by United States Patent and Trademark Office (USPTO) over 1926-2011. We use the KPSS patent data rather than NBER patent data, because the KPSS patent data enable us to identify comprehensive patent portfolios of the firms that filed application up to 2009, which are granted up to 2011. The NBER patent data contain patents that have been granted up to 2006 and most of them had application dates up to 2004. Since our BoardEx sample starts from 1999, using the KPSS patent data increases our sample size significantly.[78] The KPSS patent data provides PERMNO for the assignees of each patent. We use this to merge the patent data with BoardEx as well as Compustat and CRSP. In the base case analysis,

[78]Although BoardEx data starts from 1997, data prior to 1999 is sparse (e.g., see Engelberg, Gao and Parsons (2013)).

we assign zero patents to firms in the BoardEx sample without any patenting activity. The final BoardEx-KPSS Patent-Compustat-CRSP merged file leaves us with 6,504 unique firms.

Using the BoardEx employment history file, we identify all the managers in each matched company for each year from 1999 to 2009. We obtain the sample of senior managers from BoardEx, which we define as managers with a title of VP or higher. The senior managers in our sample can be broadly categorized in seven groups: CEOs, presidents, chairmen, other chief officers (CFO, CIO, etc.), division heads, VPs, and others. We exclude all firm-years that have the following characteristics: (i) there is only one manager in the management team (since it is unlikely that large firms covered by BoardEx have only one senior manager); (ii) there is no CEO for a firm in a certain year; (iii) there are more than 30 senior managers in the management team (suggesting that perhaps certain titles are misleading and we are overclassifying senior managers); (iv) financial and utility firms, defined by SIC code from 6000 to 6999 and from 4901 to 4999, respectively; and (v) firm-years with missing values for the relevant variables that we need to use. After these exclusions, we are left with 30,432 firm-year observations for 4,389 firms.

We then obtain the demographic and education information for each senior manager from the BoardEx database. To obtain education-based connections, we classify all the graduate degrees into four different categories: business school (MBAs included), medical school, law school, and other graduate (see, Cohen, Frazzini, and Malloy (2008)).

3.3.2 Measures of Management Quality

3.3.2.1 Individual Proxies for Management Quality

We measure management quality and reputation along two dimensions. The first is management team resources, which refers to the human and knowledge resources (including both education and relevant work experience) available to firm management. The second is based on connections available to firm management, which capture their ability to reach out to managers in other firms, thus enabling them to obtain not only valuable information from other firm managers, but also better terms when dealing with these firms as customers or suppliers.

The management team resources available to the firm depend in part upon the number of people in its management team. Therefore, our first measure of team resources is the size of the firm's top management team (*Team Size*), measured by the number of officers with the rank of vice president or higher. Management team resources also depend upon the knowledge and education of its members. Thus, our second measure of management team resources is the percentage of the management team with an MBA degree (*MBA*). A larger management team and a higher percentage of the team with MBA degrees imply better management quality. Our third measure is the fraction of the top management team with a Ph.D. degree. In some innovative firms (e.g., technology or biotech firms), some of the top management team may have Ph.D. degrees, which may help them in choosing the appropriate innovative projects for their employees to work on (even if they themselves are not personally involved in developing the innovation) as well as for hiring the "right" employees (scientists and engineers) who may develop innovation for their firm. Another contributing factor that increases management team resources is relevant work experience, which we measure in two ways. First, we look at the percentage of the management team who have served as vice presidents or higher prior to joining the current firm (*Prior Work Experience*). Second, we also use the number of outside board positions that each manager has served on averaged across all managers (*Prior Board Experience*). Clearly, prior board experience can also be a useful asset when managing a firm, since managers may have acquired experience in solving important problems when serving as board members of previous firms that they have worked for. In summary, the greater the value of the above variables, the better is the management quality. Three of the above proxies (*Team Size*, *MBA*, and *Prior Work Experience*) are similar to those used by Chemmanur and Paeglis (2005) and Chemmanur, Paeglis, and Simonyan (2011).

We measure management connections in two ways. First, we look at connections built up by members of the management team based on their work experience so far (*Employment Connections*). For each manager, total employment-based connection is calculated as the number of senior managers or directors that each senior manager in the management team has worked with so far. If individuals have worked together in the same company previously during an overlapping time period, they are defined as connected. In summary, the variable *Employment Connections* is defined as the number of employment-based connections of the top management team divided by *Team Size*. Second, we look at the connections built up by members of the firm's top management team during their graduate education, which may often last through their entire career (*Education Connections*). For each manager, total education-based connection is calculated as the number of senior managers or directors that each senior manager in the management team has been in graduate school with. If individuals study in the same educational institution, have degrees in the same education category (described above), and graduate within one year of each other, they are defined as connected. In summary, the variable *Education Connections* is defined as the number of education-based connections of the top management team divided by *Team Size*.

In addition, we create the variable *Average Tenure* as the average number of years that each senior manager has worked in a firm, and use it as a control variable.

Table 1 provides summary statistics on the management quality measures that we describe above. For the median firm in our sample, there are seven senior managers in the management team; 20 percent of the senior management team has an MBA degree; 10 percent of the senior management team has prior work experience as a senior manager at another firm; zero percent of the senior management team have sat on boards of other firms; and zero percent of the senior management team has a PhD degree. The median level of *Education Connections* is zero and that of *Employment Connections* is 15.4. The median number of years that each manager has worked in a firm is 5.2 years.

3.3.2.2 Common Factor Analysis on Individual Management Proxies

Each of the variables (proxies) described above is likely to have its unique limitations as a measure of the underlying management quality, and is therefore unlikely to be a comprehensive measure of management quality by itself. Therefore, we use common factor analysis to capture the variation common to our seven observable measures of management quality. More precisely, the aim of our factor analysis is to account for, or explain, the matrix of covariances between our individual management quality measures using as few factors as possible. Next, we rotate the initial factors so that each individual management quality measure has substantial loadings on as few factors as possible. This methodology is consistent with the implementation of common factor analysis in the literature.[79]

All the management quality measures are aggregated to the level of the management team, and are likely to be correlated with firm size. Therefore, in order to ensure that these measures are independent of firm size, we use firm size and industry-adjusted variables in our common factor analysis. Specifically, we conduct the following regression for each of the six proxies of management quality:

$$Measure_{i,t} = \alpha[Ln(firm\ size)_{i,t}] + \beta[Ln(firm\ size)_{i,t}]^2 + Industry\ FE + Year\ FE + \epsilon_{i,t}, \tag{3.1}$$

where i indexes the firm and t indexes the year of the observation. Industry (defined at 2-digit SIC code level) and year fixed effects are included. We use the residuals from the above regression as the firm size- and industry-adjusted measures of the management quality.

Table 2 presents the results of the common factor analysis. The common factor analysis leads to seven factors. Panel A of Table 2 reports the eigenvalues of each factor. Factors with

[79] We adopt common factor analysis rather than principal component analysis as our method of choice for identifying a single management quality factor. The aim of common factor analysis is to account for or to "explain" the matrix of covariances between our seven individual management quality proxies using the minimum number of factors. In contrast, the aim of principal component analysis is to break down the above covariance matrix into a set of orthogonal components equal to the number of the individual proxies. Given that our objective here is to identify a factor that embodies the underlying unobservable construct, namely, "management quality," we believe that the former method is more appropriate here.

higher eigenvalues account for a greater proportion of the variance of the observed variables. Only the first factor has an eigenvalue that is larger than one. Further, we find that this first factor explains 80 percent of the variation of our individual management quality proxies (the eigenvalue of the first factor as a proportion of the sum of the eigenvalues of all seven factors). This suggests that the first factor is the most important one, providing us with a distinct (unique) measure of management quality. We term this factor the management quality factor (MQF).[80]

Factors with higher eigenvalues account for a greater proportion of the variance of the observed variables. Only the first factor has an eigenvalue that is greater than one. This suggests that the first factor is the most important, providing us with a distinct measure of management quality. We term this factor the management quality factor (MQF).[81]

Panel B reports the loadings on the first factor for each individual management quality variable. The loadings indicate that all individual management quality measures load positively on the first factor. Consistent with this, the second column of Panel B finds positive correlations between the first factor and each of the seven management quality measures. The third column of Panel B of Table 2 reports the communality of each variable with the common factor, which measures the proportion of the variance of each variable that is accounted for by the common factors. Communality is bounded between zero and one, and higher values indicate that a larger proportion of the variation in the variable is captured by the common factors.

[80] In a robustness check that we describe later, we address the possibility that our results are driven by the presence of *Team Size* in the management quality factor, and not the other quality measures. To address this concern, we recalculate the management quality factor by excluding *Team Size* from the common factor analysis. We show that our results are similar when we use the first factor derived from this alternative model.

[81] In a robustness check that we describe later, we address the possibility that our results are driven by the presence of *Team Size* in the management quality factor, and not the other quality measures. To address this concern, we recalculate the management quality factor by excluding *Team Size* from the common factor analysis. We show that our results are similar when we use the first factor derived from this alternative model.

3.3.2.3 Validity of Management Quality Factor

This subsection addresses the concern whether management quality factor (MQF) actually measures the quality of a management team. If MQF actually captures the overall quality of the management team, one immediate implication is that management teams with higher MQF should be paid more than those with lower MQF. To test this implication, we make use of the compensation data in the BoardEx database. BoardEx provides the annual compensation information for a firm's senior managers, which includes salary, bonus, the value of shares awarded, value of LTIP (Long Term Incentive Plan) awarded, and value of options awarded at the manager-firm-year level. However, the coverage of the compensation data is smaller than the coverage of individual measures that are used to calculate MQF, as the compensation information of many managers is missing in BoardEx. We therefore only focus on the managers that have available compensation information in BoardEx.

For each firm, we construct three different measures of compensation: *Average Total Compensation*, *Average Cash Compensation*, and *Equity Compensation/Total Compensation*. *Average Cash Compensation* is defined as the average amount of cash compensation for a management team, where cash compensation includes base cash salary and bonus. *Average Total Compensation* is defined as the average amount of total compensation for a management team, where total compensation, in addition to cash compensation, also includes the equity compensation, consisting of the value of shares awarded, the value of LTIP awarded, and the value of options awarded. *Equity Compensation/Total Compensation* is defined as the fraction of equity compensation out of total compensation. We test the following model:

$$Ln(Compensation_{i,t}) = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t}, \qquad (3.2)$$

where $Ln(Compensation_{i,t})$ are the natural logarithm of the above three compensation measures for the management team in firm i in year t. We take logs due to the right skewed distribution. Z is a set of control variables, which is described in details in Section 3.3.5. We report the results for the above regressions in Table 3. Columns (1)-(3) present regression results with the average total compensation, average cash compensation, and fraction of equity compensation out of total compensation as the dependent variables, respectively. As we expected, the coefficients on MQF are positive and statistically significant at the 5% level for two out of three specifications. The economic magnitude of the effect of MQF is significant as well. For instance, a one inter-quartile range increase in MQF is associated with 5.8% increase in the average total compensation The positive and significant relationship between our MQF and management team compensation suggests that MQF is a valid measure for management quality.

3.3.3 Measures of Innovation

Following the existing literature (e.g., Kogan, Papanikolaou, Seru, and Stoffman (2012); Seru (2014)), we use patent-based metrics to capture firm innovativeness. While we also use R&D expenditures as a measure of investments in innovative activity, patent-based measures are widely-used proxies of innovation output. We obtain patent data from the database created by KPSS. This database provides detailed information of more than six million patents granted by the USPTO from 1926 to 2011. KPSS have matched assignees in the patent data set with CRSP PERMNOs if the assignee is a public corporation or subsidiary of a public corporation.

Patent data are subject to two types of truncation problems. First, patents are recorded in the dataset only after they are granted and the lag between patent applications and patent grants is significant (about two years on average). As we approach the last few years for which there are patent data available, we observe a smaller number of patent applications that are eventually granted. Many patent applications filed during these years were still under review and had not been granted by 2011. We partially mitigate this bias by restricting our analyses to two years before the patent data ends (i.e., in 2009). Further, following Hall, Jaffe, and Trajtenberg (2001) and Seru (2014), we correct this bias 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. The second type of truncation problem is stemming from citation counts. Patents tend to receive citations over a long period of time, so the citation counts of more recent patents are significantly downward biased. Following Hall, Jaffe, and Trajtenberg (2001) and Seru (2014), this bias is accounted for by scaling citations of a given patent by the total number of citations received by all patents in that year in the same 3-digit technology class as the patent. Note that the above methodology gives us class-adjusted measures of patents and citations, which adjust for trends in innovative activity in particular industries.

We construct three measures for a firm's annual innovative output based on the patent application year.[82] The first measure, *Ln(Patents)*, is the natural logarithm of one plus the class-adjusted patent count for a firm in a given year. Specifically, this variable counts the total number of (class-adjusted) patent applications filed that year that were eventually granted. However, a simple count of patents may not distinguish breakthrough innovations from incremental technological discoveries. Therefore, we consider two additional measures. The second measure, *Ln(Citations)*, is the natural logarithm of one plus the class-adjusted total number of citations received by the firm's patents filed in a given year. The third measure, *Ln(Citations/Patent)*, is constructed by taking natural logarithm of one plus the total number of class-adjusted citations a firm receives on all the patents it applies for in a given year and normalizing it by one plus the total number of class-adjusted patents applied for in that year. We take the natural logarithm because the distribution of patents and citations are right skewed. To avoid losing observations with zero patents or zero citations, we add one to the actual values. Table 1 reports the summary statistics of our innovation measures. The median R&D to assets (*R&D/Assets*) ratio in our sample is 1 percent. Further, an average (median) firm in our sample has 0.860 (0) class-adjusted patent. An average (median) firm in our sample has 0.034 (0) class-adjusted citation.

[82]Consistent with the innovation literature (e.g., Griliches, Pakes, and Hall (1988)), the application year is more relevant for our purposes than the grant year since it is closer to the time of the actual innovation.

3.3.4 Measures of Inventor Mobility

To identify the inventor mobility, we collect inventor information of each patent from the U.S Patent Inventor Database (1975-2010) (provided by Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014)) from the Harvard Business School Dataverse. The U.S. Patent Inventor Database includes inventor names, inventor addresses, assignee names, application and grant date for each patent. More importantly, it identifies unique inventors over time so that we could possibly track the moves of each inventor. Following Marx, Strumsky, and Fleming (2009), we identify mobile inventors as changing employers if he has ever filed two successive patent applications that are assigned to different firms (or organizations). As we need at least two patents to detect a move, inventors that have filed a single patent throughout their career are necessarily excluded from our analysis.

For a given firm, an inventor's move-in year is the year when he filed his first patent in this firm; the inventor's move-out year is that when he filed his first patent in the subsequent firm. For the inventor's very last employer, we assume that the inventor stayed with that firm and did not move out.[83] For example, in the inventor database, an inventor named Christopher L. Holderness filed two patent applications till 2010. He filed patent applications with Corning Inc. in 1999 and then with Dell Inc. in 2003. Thus, for Corning, Mr. Holderness's move-in year is 1999 and move-out year is 2003; and for Dell, Mr. Holderness's move-in year is 2003, and he has stayed with Dell since 2003. Once we identify each mobile inventor's move-in and move-out year, we aggregate the number of mobile inventors that move in and move out at the firm-year level to obtain the total inflows and outflows of mobile inventors for a given firm in a year. We define the difference between the natural logarithm of one plus the inflow and the natural logarithm of one plus the outflow as the net inflow of mobile inventors ($Net\ Inflow_t$).

To examine the moves of inventors with different innovative ability, we classify the

[83] As a robustness check, we redefine the dates that the inventor moved out of his last employer as one or two years after he filed his last patent in that firm. Our results remain qualitatively similar with this alternative definition.

mobile inventors into two groups, namely, high-quality and low-quality inventors. For each inventor, we look at the average quality of his historical patents, i.e., the citations per patent for all the patents he filed prior to the current year. If an inventor's historical citations per patent is higher than the sample median, he is considered as a high-quality inventor; otherwise, he is a low-quality inventor. We aggregate the mobility measures of high-quality (low-quality) inventors at the firm-year level to get the annual inflow and outflow of the high-quality (low-quality) inventors for a firm.

We use the quality of incoming (outgoing) inventors as in a given year as another measure of the quality of inventors joining (leaving) a firm. Specifically, the measure of average quality of incoming inventors for firm i in year t, $\textit{Incoming Quality}_{i,t}$, is the natural logarithm of one plus the average historical citations per patent of all inventors that move into the firm in year t. The measure for average quality of outgoing inventors for firm i in year t, $\textit{Outgoing Quality}_{i,t}$, is the natural logarithm of one plus the average historical citations per patent of all inventors that move out. $\textit{Net Quality Change}_{i,t}$ is defined as the difference between $\textit{Incoming Quality}_{i,t}$ and $\textit{Outgoing Quality}_{i,t}$, which captures the change in inventor quality at the firm-year level.

3.3.5 Other Variables

Following the innovation literature, we obtain firms' financial information from Compustat and price data from CRSP and control for a number of firm characteristics that could affect firms' innovation output. We compute all variables for firm i over its fiscal year t. The controls include *Ln(Assets)*, which is the natural logarithm of book value of total assets; *M/B*, which is the Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA*, which is defined as operating income before depreciation divided by total assets; *CAPEX/Assets*, which is defined as capital expenditures over total assets; *HHI*, which is the value of Herfindahl-

Hirschman Index in the firm's industry (defined at the 2-digit SIC code level) in each year; *Stock Return*, which is the firm's prior 12 months annual compounded stock return; and *Average Tenure*, which is the average number of years that each manager has worked in a firm. To minimize the effect of outliers, we winsorize all independent variables at the 1st and 99th percentiles. Table 1 provides summary statistics for the control variables described above. Median firm size in our sample is $323 million, suggesting that our sample consists of mainly mid-size and large firms. The median firm in our sample has an ROA of 10.2%, CAPEX-to-assets ratio of 3.5%, Tobin's Q of 1.6, and annual stock return of 3.3%.

3.4 Empirical Tests and Results

3.4.1 The Effect of Management Quality on R&D Expenditures

We expect that firms with higher quality management teams are likely to devote a greater amount of resources to innovative activities, i.e., management quality is positively associated with innovation input. In this section, we empirically test this hypothesis (**H1**) by estimating the following regression:

$$R\&D/Assets_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t}, \tag{3.3}$$

where i indexes firm and t indexes time and n equals one, two or three. The management quality measure, *MQF* is measured for firm i over its fiscal year t. Z is a vector of control variables that could affect a firm's innovation output, which includes *Ln(Assets)*, *M/B*, *ROA*, *CAPEX/Assets*, *Stock Return*, *HHI*, and *Average Tenure*. We include year dummies and 2-digit SIC industry dummies.[84,85] In all regressions throughout the paper, standard errors are clustered at the firm level.

[84] Our results are insensitive to defining industry dummies at 3-digit or 4-digit SIC code level.

[85] For robustness, we also examine the same regressions controlling for industry, year and state fixed effects, industry×year fixed effects, and industry×state×year fixed effects. We report results controlling for industry×state×year fixed effects in Table A3 in the Internet Appendix. We find that the results remain qualitatively similar to those reported here.

Table 4 reports the regression estimation results for regression (3.3). Columns (1)-(3) correspond to R&D to assets ratios of one, two and three years ahead of the year in which management quality (i.e., MQF) is measured. The coefficients of MQF in all three specifications are positive and both statistically and economically significant. For example, the coefficient in Column (1) suggests that a one inter-quartile range increase in MQF is associated with an increase of 0.74 percentage point in $R\&D/Assets$ for next year, which is equivalent to 70% of the sample median. These results suggest that a firm's innovation input, as measured by R&D expenditures, is positively associated with its management quality, consistent with hypothesis **H1**.

3.4.2 The Effect of Management Quality on Corporate Innovation

In this section, we test the relationship between management quality and corporate innovation output, in terms of both quantity (as measured by the number of patents) and quality (as measured by citations and citations per patent), which corresponds to our second hypothesis (**H2**). We estimate the following models:

$$Ln(Patents)_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t}, \quad (3.4)$$

$$Ln(Citations)_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t}, \quad (3.5)$$

$$Ln(Citations/Patent)_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ FE + Year\ FE + \epsilon_{i,t}, \quad (3.6)$$

where i indexes firm and t indexes time and n equals one, two or three. Since the innovation process takes time, we examine the effect of a firm's management quality on its innovation as of one, two, and three years after the year in which MQF is measured. Z is the set of control variables similar to those in the previous section, but now also includes *R&D/Assets.*

Panels A, B, and C of Table 5 report the OLS estimation results for regressions (3.4), (3.5) and (3.6), respectively. Across all specifications, the coefficients on MQF are positive and significant, both statistically and economically.[86] For example, Column (1) in Panel A of Table 5 suggests that a one inter-quartile range increase in *MQF* is associated with a 12.8% increase in the next year's adjusted number of patents. Table 6 reports the results for regressions where we regress the three innovation output measures on each individual management quality measure.[87] Specifically, we use the values of *Team Size*, *MBA*, *PhD*, *Prior Work Experience*, *Prior Board Experience*, *Employment Connections*, and *Education Connections* as independent variables in Columns (1) through (7) across all panels in Table 6.[88] Except for *Prior Work Experience* and *Prior Board Experience*, we find positive and significant effects of each individual management quality measure on all three innovation output measures. These effects are economically significant as well. For instance, a one inter-quartile range increase in *MBA* corresponds to a 4% increase in patenting activity. The findings in this section support our hypothesis **H2**, that is, management quality has a positive impact on the quantity and quality of the firm's innovation output.

3.4.3 Identification: Instrumental Variable Analysis

We empirically test whether there is a link between management quality and corporate innovation. Therefore, for our baseline analyses, we conduct OLS regressions of our innovation measures on our management quality measures described above. However, the management quality of a firm may be endogenously related to corporate innovation. For instance, higher quality managers may choose to work for higher quality firms. In other words, there may be endogenous matching between management quality and firm quality. In order to address the above endogeneity concern, we use an instrumental variable (IV) analysis.

The instrument in our IV analysis is motivated by the following facts. First, incoming managers often come from established firms, and these firms are dominant players in the

[86] In a robustness check we describe later, we conduct these regressions using the sample of firms that have filed at least one patent application throughout our sample period of 1999-2009. Our results (see Table A1 in the Internet Appendix) are qualitatively similar to those reported here.

[87] Note that the coefficients and standard errors in Panel C of Table 6 are multiplied by 100 for ease of reading.

[88] Our results are qualitatively similar when we use size-adjusted individual management quality measures.

acquisition market. In other words, there is a strong correlation between the movement of managers across firms and the number of acquisitions in the industry the firm belongs to. Inspired by Ewens and Marx (2014), we count the number of acquisitions of public targets made by established firms in the industry the sample firms belong to five years prior as a proxy for the shock to the supply of outside managers in that industry.[89] The five-year lag stems from the popular retention contracts employed by the acquirers for target firms. These contracts often compensate the managers of target firms for lost compensation for up to five years and provide strong incentives for these managers to stay with the target firms for another few years. The expiration of these contracts generates a source of variation to the supply of managers available for hire. Second, the enforceability of non-compete clauses, which are commonly used in employment contracts for top management and prohibit them from joining or founding a rival company within one to two years of leaving, affects the mobility of managers across the firms.[90] Bishara, Martin, and Thomas (2015) analyze an extensive sample of CEO employment contracts and show that 80% of these contracts contain non-compete clauses, often with a broad geographic scope. A growing body of work (e.g., Garmaise (2009) and Marx, Strumsky, and Fleming (2009)) shows that higher enforceability of these non-compete clauses constrains employees' mobility (including those of managers). The enforceability of such non-compete clauses exhibits both cross-state and time series variation, which leads to variation in the mobility of managers that is unlikely to be related to corporate innovation. Based on the above facts, we construct an instrumental variable which proxies for a plausibly exogenous shock to the supply of managers available for hire by firms, making use of the strong correlation between industry acquisitions and the movement of top managers as well as the exogenous variation in the ability of managers to move.

Specifically, the instrumental variable for the management quality (MQF) of the top

[89] In an alternative specification, we also used the number of acquisitions during the two to five year period prior to the current year and find broadly similar results.

[90] Since these non-compete clauses become operational only when top managers leave their prior firms, the enforceability of these non-compete clauses can be thought as a measure of the friction facing top managers when they attempt to join the current firm.

management team in a firm i in industry j in year t is computed as follows:

$$Instrument_{j,t} = \sum_{s} Acquisitions_{j,s,t-5} \times (-Enforceability\ Index_{s,t}), \tag{3.7}$$

where j, s, and t index industry, state, and year, respectively. $Acquisitions_{j,s,t-5}$ is the number of acquisitions made by established (public) companies in industry j in state s in year $t-5$. The information on mergers and acquisitions required to construct this variable is collected from the SDC Mergers & Acquisitions Database. Again, the five-year lag allows for the expiration of retention contracts that work as "golden handcuffs" for managers and thus $Acquisitions_{j,s,t-5}$ works as a measure for the supply of managers from state s in industry j in year t.

$Enforceability\ Index_{s,t}$ is the index on the enforceability of non-compete agreements generated by Garmaise (2009).[91] It ranges from zero (e.g., California) to nine (e.g., Florida after 1997), and higher values of this index for a state indicates higher enforceability of the non-compete agreements and thus less mobility of the managers from this state. The multiplication term, $Acquisitions_{j,s,t-5} \times (-Enforceability\ Index_{s,t})$, therefore proxies for the supply of managers who are able to move across firms and available for hire from state s in industry j in year t. We then aggregate this variable at the industry-year level and use this as an instrument for top management quality in a firm in industry j in year t. We expect higher values of this instrument to be positively correlated with top management quality (MQF).

To instrument for the management quality (MQF) of firm i in industry j in year t, we

[91] Garmaise (2009) considers 12 questions analyzed by Malsberger (2004), which is the central resource describing noncompetition law in 50 US states and the DC, and assigns 1 point to each jurisdiction for each question if the jurisdiction's enforcement of that dimension of noncompetition law exceeds a certain threshold.

therefore run the first-stage regression as follows:

$$\begin{aligned} MQF_{i,j,t} &= \alpha + \beta Instrument_{j,t} + \delta Acquisitions_{j,t-5} \\ &\quad + \gamma Z_{i,t} + Industry\ FE + Year\ FE + State\ FE + \epsilon_{i,t}. \end{aligned} \tag{3.8}$$

In both the first and second stages of our IV regressions, we include the total number of acquisitions in the sample firm's industry five years prior ($Acquisitions_{j,t-5}$) to control for the effect of an industry wide shock (e.g., merger waves) on innovation. We also include fixed effects for the state in which the firm is headquartered to alleviate the concern that the relation between top management quality and innovation may be driven by other state-level factors. We expect the instrument to be positively and significantly related with our management quality factor, thus satisfying the relevance condition of a valid instrument. Further, since we control for the direct effect of merger waves on innovation, our instrument is unlikely to affect innovation through channels other than through affecting the supply of managers. Therefore, the exclusion restriction is also likely to be satisfied.

Column 1 of Panel A in Table 7 reports the results of the first stage of our IV analysis. The coefficient of the instrument is positive (as predicted) and is statistically significant at the one percent level. The first-stage F-statistic is 40.09, which is significant at the one percent level. These findings confirm that the relevance condition for the instrument is satisfied. Columns (2)-(5) of Panel A report the second-stage results of our 2SLS regressions using one, two, and three year ahead patent counts as our dependent variables. Panel B and Panel C correspond to second-stage results using the total number of citations and the number of citations per patent as dependent variables, respectively. We find that, after controlling for the potential endogeneity between *MQF* and innovation using our IV analysis, our management quality factor still has a significantly positive impact on firms' patent counts, total number of citations, and citations per patent in all specifications. Broadly, our results suggest that management quality is positively and causally related to the quantity and quality of firms' innovation output.

3.4.4 The Effect of Management Quality on Innovative Efficiency

Having established that firms with higher quality management teams are characterized by greater innovation input as well as greater innovation output and higher quality innovation output, we move on to test whether such firms are able to use R&D resources more efficiently in producing innovation output. This corresponds to our third hypothesis (**H3**). We construct two measures for innovative efficiency for our empirical tests. Following Hirshleifer, Hsu, and Li (2013), innovative efficiency here refers to the ability of the firm to generate patents and citations per dollar of R&D expenditures. The two measures for innovative efficiency, $Patents/R\&D$ ($Citations/R\&D$) is the natural logarithm of one plus the ratio of adjusted patent counts (adjusted number of citations) scaled by firm's R&D capital in the past five years. Following Chan, Lakonishok, and Sougiannis (2001) and Lev, Sarath, and Sougiannis (2005), we define a firm's R&D capital as cumulative R&D expenses assuming an annual depreciation rate of 20%. Specifically, they are defined by the following formula:

$$Patents/R\&D_{i,t} = Ln(1 + \frac{Patents_{i,t}}{\sum_{k=0}^{4}(1 - 0.2 * k) * R\&D_{i,t-k}}), \tag{3.9}$$

$$Citations/R\&D_{i,t} = Ln(1 + \frac{Citations_{i,t}}{\sum_{k=0}^{4}(1 - 0.2 * k) * R\&D_{i,t-k}}), \tag{3.10}$$

where $Patents_{i,t}$ and $Citations_{i,t}$ denote the adjusted number of patents that firm i filed in year t and the adjusted number of citations received by those patents; $R\&D_{i,t}$ denotes firm i's R&D expenses in fiscal year t.

Table 8 reports the OLS regression results for the effect of management quality on innovative efficiency.[92] Columns (1)-(3) correspond to regressions using $Patents/R\&D$ one, two and three years from now as dependent variables, respectively. Columns (4)-(6) correspond

[92] This table does not have *R&D/Assets* as a control since the dependent variable is already normalizedby R&D expenditures. In unreported tests, we control these regressions for *R&D/Assets* and find qualitatively similar results. Results available from authors upon request.

to regressions using $Citations/R\&D$ one, two, and three years from now as dependent variables, respectively.[93] We find the coefficients on management quality factor are positive and significant across all specifications. We also conduct IV analyses for innovative efficiency using the same instrumental variables as described in earlier sections.[94] In untabulated results, we find that the coefficients of *MQF* for these regressions remain positive and statistically significant. Collectively, our evidence indicates that firms with higher management quality are better at getting more "bang for the buck," i.e, use R&D resources more efficiently in generating higher innovation output.

3.4.5 The Effect of Management Quality on Corporate Innovation: Interaction Tests

In this section, we dig deeper into whether the relation between management quality and innovation productivity is stronger in some industries than in others. We thus conduct interaction tests based on hypotheses **H4** and **H5**, which predict that management team quality will have a stronger effect for firms in financially constrained industries and for firms in more competitive industries, respectively. In order to test the above hypotheses, we first interact *MQF* in our regressions with *Constrained*, a dummy variable that is equal to one if the firm operates in an industry for which the median value of external financial dependence (as calculated in Rajan and Zingales (1998)) is positive and zero otherwise. Also, we interact *MQF* with *HHI*, which is the value of Herfindahl-Hirschman Index in the firm's industry (defined at the 2-digit SIC code level) in each year.

Table 9 reports the results for the interaction tests with one year ahead innovation measures as dependent variables. Columns (1), (2), and (3) report the regression results for the interaction of *MQF* and *Constrained* as well as *Constrained* as additional independent variables. The coefficient estimates on *MQF* are significantly positive for all three measures

[93] Note that the coefficients and standard errors in Columns (4)-(6) of Table 8 are multiplied by 100 for ease of reading.

[94] The IV regression results for innovative efficiency are not reported in order to save space. These results are available from authors upon request.

of innovation output, consistent with our previous results. More importantly, the coefficients on the interaction term (*MQF*×*Constrained*) are also significantly positive for *Ln(Patents)* and *Ln(Citations)* at the one percent level. This evidence suggests that firms with higher quality management are able to select better projects, use resources more efficiently, and generate greater innovation output in adverse financing environments.

We report results of the interaction tests for *MQF* and *HHI* in Columns (4), (5), and (6) in Table 9. As before, the coefficient estimates on *MQF* are significantly positive for all three innovation measures. Further, the coefficients on the interaction term (*MQF*×*HHI*) are negative and significant, indicating that the positive impact of management quality on innovation becomes more pronounced as industry competition increases. Thus, the results in this section are consistent with our hypotheses **H4** and **H5**.

3.5 Possible Mechanisms: Inventor Mobility

Our evidence thus far is consistent with management quality having a positive relation with corporate innovation. In this section, we discuss the possible underlying mechanisms through which this may occur. As argued before, higher quality management teams may provide more R&D resources, manage R&D resources better, and provide a more risk-tolerant climate for inventors to succeed in. This, in turn, may make firms with higher management quality more attractive to higher quality inventors. Thus, one way that higher quality management teams may enhance innovation is by hiring more and higher quality inventors to work for the firm. We test these conjectures below.

3.5.1 Management Quality and Net Inflow of Inventors

To assess the relation between management quality and the net inflow of inventors that move into the firm at the firm-year level, which corresponds to our hypothesis **H6**, we test the following model:

$$Net\ Inflow_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ FE + Year\ FE + State\ FE + \epsilon_{i,t}, \quad (3.11)$$

where i indexes firm and t indexes time and n equals one, two or three. Z is a vector of control variables used in prior tests. As before, we include year dummies and 2-digit SIC industry dummies. Moreover, since location may impact inventors' decisions of moving into or out of a firm, we include state dummies for the state of the firm's headquarter in all regressions in this section.

Table 10 reports results for the above model. Across all specifications, the coefficients of interest on *MQF* are significantly positive. For instance, Column (1) of Table 10 suggests that a one inter-quartile range increase in *MQF* is associated with 0.05 increase in *Net Inflow*. The economic magnitude of the effect is large given that the sample mean of *Net Inflow* is 0.21. These findings support our hypothesis **H6**, and suggest that one mechanism through which higher quality management teams enhance firm innovation is by attracting more inventors to work for the firm.

In an untabulated analysis, we include the net inflow of inventors in the OLS regressions for the innovation output of firms. Therefore, we regress our innovation measures on the net inflow of inventors and our management quality factor (*MQF*), while including the same of set of control variables as in Table 5, year fixed effects, industry fixed effects, and state fixed effects. This test allows us to check whether *MQF* still has a direct (residual) effect on innovation after controlling for the net inflow of inventors. We find that, whereas the coefficient estimates on the net inflow of inventors are all positive and significant, the coefficients on *MQF* are still positive and significant at the one percent level. However, the magnitudes of the coefficient estimates on *MQF* are reduced quite substantially once we include the net inflow of inventors (for example, the coefficient estimate on *MQF* is decreased by 28% when $Ln(Patents)_{t+1}$ is the dependent variable and the decrease is statistically significant at the one percent level), suggesting that the effect of management quality on innovation is at least partly driven by the net inflow of inventors.

3.5.2 Management Quality and High-and Low-quality Inventors

In this section, we move on to test whether higher quality managers are better at attracting higher quality inventors. Specifically, we test the following models:

$$\begin{aligned} \textit{Net Inflow of High}_{i,t+n} = & \alpha_H + \beta_H MQF_{i,t} + \gamma_H Z_{i,t} + \textit{Industry FE} + \textit{Year FE} \\ & + \textit{State FE} + \epsilon_{i,t}, \end{aligned} \tag{3.12}$$

$$\begin{aligned} \textit{Net Inflow of Low}_{i,t+n} = & \alpha_L + \beta_L MQF_{i,t} + \gamma_L Z_{i,t} + \textit{Industry FE} + \textit{Year FE} \\ & + \textit{State FE} + \epsilon_{i,t}, \% \end{aligned} \tag{3.13}$$

where i indexes firm and t indexes time and n equals one, two or three. The same vector of control variables and same set of dummy variables are included as in the prior section. We also statistically test whether the coefficient on MQF in the regression (3.12) is positive and significantly larger than that in regression (3.13), i.e., $\beta_H > 0$ and $\beta_H > \beta_L$.

Panel A of Table 11 reports the regression estimation results using $\textit{Net Inflow of High}_{i,t}$ and $\textit{Net Inflow of Low}_{i,t}$ as dependent variables calculated at one, two, and three years subsequent to the current year. We find that the coefficients on MQF are positive using both dependent variables, indicating that management quality has positive impacts on the net inflow of both high-quality and low-quality inventors. More importantly, the effect of MQF on the net inflow of high-quality inventors is economically 10 times larger than on the net inflow of low-quality inventors across all time horizons. We test the statistical significance of the difference for the coefficients on MQF for high quality versus low quality inventors and report the test results in Panel B of Table 11. All the differences are statistically significant at the one percent level. Collectively, these findings provide further evidence that higher quality managers are indeed able to hire a greater number of high-quality inventors than low-quality inventors, consistent with our hypothesis **H7**.

In order to further analyze whether hiring high quality inventors is indeed a channel through which firms with higher quality management teams spur innovation, we include the net inflow of high quality inventors in the OLS regressions for the innovation output of firms. If higher quality inventors are driving the relation between management quality and innovation, we would expect that the coefficient estimates of the net inflow of high quality inventors to be significantly positive, while the magnitudes of the coefficients on MQF to be significantly lower.

Table 12 reports the results of these regressions. Panels A, B, and C use the number of patents, the total number of citations, and citations per patent as the dependent variable, respectively. The same set of control variables as in Table 5, year fixed effects, industry fixed effects, and state fixed effects are included in all the regressions in Table 12. Consistent with our conjecture, we find that the net inflow of high quality inventors is significantly positive at the one percent level in all the regressions in the above three panels. Further, the coefficients on the management quality factor (MQF) have much smaller magnitudes compared with the coefficients from regressions in which the net inflow of higher quality inventors is not included (that is, compared to our Table 5 results), suggesting that the effect of MQF on corporate innovation is partially mediated through hiring higher quality inventors. For instance, the coefficient on MQF with the subsequent year adjusted patents as the dependent variable is 0.096 when we control for high-quality inventor inflow, whereas it is 0.146 without this control (in Table 5, Panel A), reflecting a 34 percent decline. More interestingly, we find that the coefficients on MQF are smaller in the regressions where the net inflow of high quality inventors is included compared to the case where the net inflow of all inventors is included.[95] Collectively, these results provide evidence consistent with our conjecture that one mechanism through which higher quality management teams affect corporate innovation through hiring higher quality inventors.

[95] In untabulated analysis, we find that the differences between the coefficients on MQF in these two sets of regressions are statistically significant.

3.5.3 Management Quality and Average Inventor Quality

We further investigate whether management quality is positively associated with the change in the average inventor quality for a firm. As before, the quality for each inventor is measured as the citations per patent for the patents he has filed prior to the current year. To understand the effect of management quality on a firm's average inventor quality, we consider the following model:

$$\begin{aligned} \textit{Net Quality Change}_{i,t+n} =& \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry FE} + \textit{Year FE} \\ &+ \textit{State FE} + \epsilon_{i,t}. \end{aligned} \tag{3.14}$$

Recall that *Net Quality Change*$_{i,t}$ is defined as the difference between *Incoming Quality*$_{i,t}$ and *Outgoing Quality*$_{i,t}$, which captures the net change in average inventor quality of the firm's inventor team in a given year.

Table 13 reports the OLS regression results for the above model, using the the net change in average inventor quality (*Net Quality Change*) measured over the subsequent one, two and three years, respectively.[96] The coefficients on *MQF* are both positive and significant at the one percent level for all specifications. The economic magnitude of the impact is significant as well. For instance, Column (1) of Panel A suggests that a one inter-quartile range increase in *MQF* leads to a net increase in the next year's average inventor quality equivalent to 15% of the sample mean of this variable. In untabulated analyses, we conduct same tests using *Incoming Quality* and *Outgoing Quality* measured in one, two, and three years from now as the dependent variables, respectively. We find that, across all time horizons, the coefficients on *MQF* for *Incoming Quality*$_{i,t}$ and *Outgoing Quality*$_{i,t}$ are both significantly positive. This suggests that, for higher management quality firms, the newly-hired inventors as well as laid-off inventors are more innovative compared with those for lower management quality firms. Therefore, our results provide supporting evidence that higher management

[96]Note that coefficients and standard errors in Table 13 are multiplied by 100 for ease of readability.

quality is associated with a greater increase in the average inventor quality of a firm, again consistent with our hypothesis **H7**.

3.5.4 Management Quality and Corporate Innovation Strategies

In this section, we further investigate the possible differences in the innovation strategies adopted by firms with higher versus lower management quality. As we have conjectured earlier, if firms with higher quality management teams engage in more explorative innovative strategies, such firms should have a greater number of patents in the two tails of the patent quality distribution, i.e., very successful and very unsuccessful patents. On the other hand, if firms with higher quality management teams adopt more exploitative strategies, such firms will have more moderately successful patents. To understand firms' innovative strategies, we categorize our sample pool of patents applied between 1999 and 2009 in to three groups: (i) *Top 10%*, defined as patents receiving the number of citations in the top 10% among all patents in the same 3-digit technology class and application year; (ii) *No Cites*, defined as those receiving zero citation till 2009; and (iii) *Moderate Cites*, defined as those receiving at least one citation but not in the top 10%. Balsmeier, Fleming, and Manso (2014) follow a similar approach in their study of the relation between the independence of firms' corporate boards and their innovation strategies. Using the number of patents in each category, we estimate the following models:

$$\textit{Top 10\%}_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry FE} + \textit{Year FE} + \epsilon_{i,t}, \tag{3.15}$$

$$\textit{No Cites}_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry FE} + \textit{Year FE} + \epsilon_{i,t}, \tag{3.16}$$

$$\textit{Moderate Cites}_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry FE} + \textit{Year FE} + \epsilon_{i,t}. \tag{3.17}$$

Table 14 reports the results for the above regressions. Columns (1), (2), and (3) across all panels of Table 14 correspond to regression results using the natural logarithm of one plus the number of patents in the aforementioned three groups as dependent variables (*Top 10%*, *No Cites*, and *Moderate Cites*), respectively. Panels A, B, and C correspond to regression results using one, two and three year ahead dependent variables, respectively. The same set of control variables used in Table 5 are included in all specifications and coefficient estimates on the controls are not reported in order to save space (available from authors upon request). Columns (4), (5), and (6) report the tests of statistical differencew between coefficient estimates across the regression models in Columns (1), (2), and (3). In all specifications in Table 14, we find the coefficients on *MQF* are positive and statistically and economically significant. These results indicate that firms with higher quality management teams engage in both explorative and exploitative innovative strategies. Such firms are able to produce more patents in all three categories.

Further, we find that the coefficients on *MQF* in Columns (1) and (2) are significantly larger than that in Column (3), suggesting that firms with higher management quality firms may engage more in explorative innovative strategies, thus producing more patents in the two tails of the patent quality distribution. More interestingly, the coefficients in Column (1) are much bigger than those in Column (2) or (3). We also conduct IV analyses for these regressions using the same instrumental variable as described in earlier sections and the results are qualitatively similar to the OLS regression results reported in Table 14.[97] These findings suggest that management quality has a more pronounced effect on successful patents than on unsuccessful patents or average patents, i.e., firms with higher quality management teams are better at motivating successful patents that are highly cited afterwards. Broadly, the results in this section support both hypotheses **H8A** and **H8B**.

[97]The IV results for the innovative strategies are not reported in order to save space. These results are available from authors upon request.

3.6 Robustness Tests

3.6.1 Sample of Innovative Firms

We use the entire BoardEx-KPSS patent-Compustat-CRSP merged sample in our main analysis and assign zero patents to those firms without any patent record following prior studies (see, e.g., Fang, Tian, and Tice (2014) and Seru (2014)). One concern of measurement error may be that some firms in our sample may not engage in any innovative activities (i.e., such firms may not appear as a patent assignee in the patent dataset). Thus, we re-estimate our baseline regressions using a sample consisting of innovative firms only, which refer to firms that have filed at least one patent application over our sample period of 1999-2009. We therefore alleviate the measurement error concern by studying a more accurate but smaller sample. The results are reported in Table A1 of our Internet Appendix.[98] The positive relation between our management quality factor and all three measures of innovation output continue to hold in this sample.

3.6.2 Alternative Management Quality Factor

In this section, we re-run our common factor analysis using all proxies other than management team size. We do this to ensure that our results are not driven by any team size-specific effects. Thus, we re-estimate the management quality factor after excluding team size and re-run the regressions between this alternative management quality factor and corporate innovation.

The results of these tests are reported in Table A2 of our Internet Appendix. Panels A, B, and C report the OLS regression results using the number of patents, total number of citations and citations per patent as dependent variables, respectively. We find that, consistent with our previous results, all three measures of innovation output are positively related to this alternative management quality factor.

[98]While we use our full set of control variables in our regressions in Tables A1, A2, and A3, we do not show the coefficient estimates for these controls to conserve space.

3.7 Conclusion

We analyze the effect of the human capital or "quality" of the top management of a firm on its innovation activities. We extract a "management quality factor" using common factor analysis on various individual proxies for the quality of a firm's management team, such as management team size, fraction of managers with MBAs, the average employment- and education-based connections of each manager in the management team, fraction of members with prior work experience in a top management position, the average number of prior board positions that each manager serves on, and the fraction of managers with doctoral degrees. Firms with higher quality management teams not only invest more in innovation (as measured by R&D expenditures), but also have a greater quantity and quality of innovation, as measured by the number of patents and citations per patent, respectively. We control for the endogenous matching of higher quality managers and higher quality firms using an IV analysis where we use a plausibly exogenous shock to the supply of new managers available for hire by a firm (which, in turn, will affect of the quality of a firm's top management team) as an instrument for top management human capital. An important channel through which higher management quality firms achieve greater innovation success is by hiring a larger number of inventors (controlling for R&D expenditures), and also by hiring higher quality inventors (as measured by their prior record of citations per patent). Finally, we show that higher quality management team firms seem to pursue both exploratory and exploitative innovations.

While our empirical evidence suggests that higher quality managers are able to make better innovative investments and implement them more ably by (among others) hiring higher quality inventors, we do not wish claim that this is the sole channel through which higher quality top management teams are able to generate a larger number of, and higher quality, innovations for their firms. A complementary channel through which higher quality management teams may be able to generate greater innovation productivity for their firms is through greater risk-taking: higher quality managers may have less fear of failure so that they are more willing to explore, investing more in innovations. Consistent with this conjecture, there is some evidence that risk-taking CEOs influence innovation success (see, e.g., Sunder, Sunder, and Zhang (2014)). However, there is no evidence so far in the literature documenting this risk-taking channel in the context of the top management teams of firms.

References

Amornsiripanitch, Natee, Paul A. Gompers, and Yuhai Xuan, 2016, More than money: Venture capitalists on boards, Working paper, Havard Business School.

Bereskin, Frederick L., and Po-Hsuan Hsu, 2013, Bringing in changes: The effect of new ceos on innovation, Working paper, University of Delaware.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend, 2015, The impact of venture capital monitoring, *The Journal of Finance (Forthcoming)* .

Bishara, Norman D., Kenneth J. Martin, and Randall S. Thomas, 2015, An empirical analysis of noncompetition clauses and other restrictive postemployment covenants, *Vanderbilt Law Review* 68, 1–51.

Boot, Arnoud W. A., 1992, Why hang on to losers? divestitures and takeovers, *The Journal of Finance* 47, 1401–1423.

Chemmanur, Thomas J., Lei Kong, Karthik Krishnan, and Qianqian Yu, 2016, Top management human capital, inventor mobility, and corporate innovation, Working paper, Boston College.

Chemmanur, Thomas J., Karthik Krishnan, and Debarshi K. Nandy, 2011, How does venture capital financing improve efficiency in private firms? a look beneath the surface, *Review of Financial Studies* 24, 4037–4090.

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

Cornelli, Francesca, and Oğuzhan Karakaş, 2015, CEO turnover in LBOs: The role of boards, Working paper, LBS.

Cornelli, Francesca, Zbigniew Kominek, and Alexander Ljungqvist, 2013, Monitoring managers: Does it matter?, *The Journal of Finance* 68, 431–481.

Da Rin, Marco, Thomas F. Hellmann, and Manju Puri, 2013, A survey of venture capital research, in George M. Constantinides, Milton Harris, and René M. Stulz, eds., *Handbook of the Economics of Finance*, 573–648 (Elsevier, Amsterdam).

Denis, David J., and Diane K. Denis, 1995, Performance changes following top management dismissals, *The Journal of Finance* 50, 1029–1057.

Ewens, Michael, and Matt Marx, 2014, Executive replacement in venture capital-backed startups, Working paper, Caltech.

Gao, Huasheng, Jarrad Harford, and Kai Li, 2015, CEO turnover-performance sensitivities in private firms, *The Journal of Financial and Quantitative Analysis (Forthcoming)* .

Garmaise, Mark J., 2009, Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment, *Journal of Law, Economics, and Organization* 376–425.

Gorman, Michael, and William A. Sahlman, 1989, What do venture capitalists do?, *Journal of Business Venturing* 4, 231–248.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working Paper 8498, National Bureau of Economic Research.

Hellmann, Thomas, and Manju Puri, 2002, Venture capital and the professionalization of start-up firms: Empirical evidence, *The Journal of Finance* 57, 169–197.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *The Journal of Finance* 62, 251–301.

Huang, Sheng, 2014, Managerial expertise, corporate decisions and firm value: Evidence from corporate refocusing, *Journal of Financial Intermediation* 23, 348–375.

Huson, Mark R., Robert Parrino, and Laura T. Starks, 2001, Internal monitoring mechanisms and ceo turnover: A long-term perspective, *The Journal of Finance* 56, 2265–2297.

Kaplan, Steven N., and Per Strömberg, 2003, Financial contracting theory meets the real world: An empirical analysis of venture capital contracts, *The Review of Economic Studies* 70, 281–315.

Knyazeva, Anzhela, Diana Knyazeva, and Ronald W. Masulis, 2013, The supply of corporate directors and board independence, *Review of Financial Studies* 26, 1561–1605.

Lerner, Josh, 1995, Venture capitalists and the oversight of private firms, *The Journal of Finance* 50, 301–318.

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

Malsberger, Brian M., 2004, *Covenants Not To Compete: A State-by-state Survey* (Bna Books, Washington).

Manso, Gustavo, 2011, Motivating innovation, *The Journal of Finance* 66, 1823–1860.

Marx, Matt, Deborah Strumsky, and Lee Fleming, 2009, Mobility, skills, and the michigan non-compete experiment, *Management Science* 55, 875–889.

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

Oyer, Paul, and Scott Schaefer, 2011, Chapter 20 - personnel economics: Hiring and incentives, volume 4, Part B of *Handbook of Labor Economics*, 1769–1823 (Elsevier).

Pan, Yihui, 2015, The determinants and impact of executive-firm matches, *Management Science (Forthcoming)* .

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

Sörensen, Morten, 2007, How smart is smart money? a two-sided matching model of venture capital, *The Journal of Finance* 62, 2725–2762.

Stock, James H., and Motohiro Yogo, 2005, Testing for weak instruments in linear IV regression, *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* .

Tian, Xuan, 2011, The role of venture capital syndication in value creation for entrepreneurial firms, *Review of Finance* 245–283.

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

Wasserman, Noam, 2003, Founder-CEO succession and the paradox of entrepreneurial success, *Organization Science* 14, 149–172.

Weisbach, Michael S., 1988, Outside directors and CEO turnover, *Journal of Financial Economics* 20, 431–460, The Distribution of Power Among Corporate Managers, Shareholders, and Directors.

Weisbach, Michael S., 1995, CEO turnover and the firm's investment decisions, *Journal of Financial Economics* 37, 159–188.

Wooldridge, Jeffrey M., 2010, *Econometric analysis of cross section and panel data*, second edition (MIT press., Cambridge).

Table 1: Summary Statistics

This table reports summary statistics for our sample of public firms between 1999 and 2009. *Adjusted Patents* is the truncation-adjusted number of patents that a firm filed in a given year; *Adjusted Citations* is the total adjusted number of citations received by the firm's patents filed in a year; *Adjusted Citations/Patent* is the adjusted number of citations per patent for a firm in a given year. *Team Size* is the number of managers (VP or higher) in a firm's management team; *MBA* is the fraction of the managers that have MBA degrees; *Prior Work Experience* is the fraction of top managers that have experience working as VP or higher in other companies; *Education Connections* is the average number of graduate connections that each manager has through education (if two managers graduated from the same university with the same degree within one year of each other, those two are defined as connected); *Employment Connections* is the average number of connections that each manager has through prior employment (if two managers worked in the same previous company during overlapping time periods, either as managers or directors, those two are defined as connected); *Prior Board Experience* is the average number of board positions that each manager has served on; *PhD* is the fraction of the managers that have PhD degrees; *Total Assets* is the firm's total assets; *ROA* is defined as operating income before depreciation divided by total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* for an industry (defined at two-SIC digit level) in a given year is defined by the following formula: $\sum_{i=1}^{\text{number of firms in the same 2-digit industry}} \frac{(\text{firm sales}_i)^2}{(\text{industry sales})^2}$; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm.

Variable	Obs	Mean	Std.Dev.	Min	1st Quartile	Median	3rd Quartile	Max
Adjusted Patents	30432	0.862	2.308	0.000	0.000	0.000	0.309	10.439
Adjusted Citations	30432	0.034	0.108	0.000	0.000	0.000	0.000	0.495
Adjusted Citations/Patent	30432	0.002	0.006	0.000	0.000	0.000	0.000	0.025
Team Size	30432	7.751	4.469	2.000	5.000	7.000	10.000	30.000
MBA	30432	0.230	0.195	0.000	0.000	0.200	0.333	1.000
Prior Work Experience	30432	0.141	0.172	0.000	0.000	0.100	0.235	1.000
Education Connections	30432	1.417	3.296	0.000	0.000	0.000	1.200	55.500
Employment Connections	30432	17.949	11.108	1.000	10.000	15.400	23.000	98.667
Prior Board Experience	30432	0.071	0.149	0.000	0.000	0.000	0.100	2.667
PhD	30432	0.074	0.146	0.000	0.000	0.000	0.100	1.000
Total Assets (Million)	30432	2887.979	12991.060	0.306	83.810	322.609	1335.178	304594.000
ROA	30432	0.035	0.279	-2.041	0.014	0.102	0.163	0.424
M/B	30432	2.307	2.904	0.166	1.169	1.606	2.499	137.183
CAPEX/Assets	30432	0.065	0.088	0.000	0.017	0.035	0.074	0.542
R&D/Assets	30432	0.077	0.153	0.000	0.000	0.010	0.092	0.995
Stock Return	30432	0.173	0.767	-0.884	-0.289	0.033	0.404	3.458
HHI	30432	0.063	0.060	0.020	0.032	0.041	0.072	1.000
Average Tenure	30432	5.833	3.319	1.000	3.571	5.200	7.333	36.500

Table 2: Common Factor Analysis

This table reports statistics related to common factor analysis. *Factor 1- Factor 7* are the common factors obtained by using common factor analysis on the firm size- and industry-adjusted *Team Size, MBA, Prior Work Experience, Education Connections, Employment Connections, Prior Board Experience*, and *PhD*. *Team Size* is the number of managers (VP or higher) in a firm's management team; *MBA* is the fraction of the managers that have MBA degrees; *PhD* is the fraction of the managers that have PhD degrees; *Prior Work Experience* is the fraction of top managers that have experience working as VP or higher in other companies; *Prior Board Experience* is the average number of board positions that each manager has served on; *Employment Connections* is the average number of connections that each manager has through prior employment (if two managers worked in the same previous company during overlapping time periods, either as managers or directors, those two are defined as connected); *Education Connections* is the average number of graduate connections that each manager has through education (if two managers graduate from the same university with the same degree within one year of each other, those two are defined as connected). Panel A reports the eigenvalues for the seven factors to mimic the correlation matrix of the original variables. Panel B reports the loadings on the first factor and the correlation with the first factor as well as communality of the original variables. Panel C reports the descriptive statistics of the first factor.

Panel A: Eigenvalues

Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
1.172	0.577	0.216	0.042	-0.022	-0.195	-0.301

Panel B: Summary For Factor Analysis

Variable	Loadings On First Factor	Correlation with First Factor	Communality
Team Size	0.513	0.841	0.264
MBA	0.141	0.078	0.020
PhD	0.053	0.038	0.003
Prior Work Experience	0.368	0.233	0.135
Prior Board Experience	0.288	0.094	0.083
Employment Connections	0.803	0.906	0.645
Education Connections	0.149	0.086	0.022

Panel C: Summary Statistics of First Factor

Obs	Mean	Std.Dev.	Min	1st Quartile	Median	3rd Quartile	Max
30432	0.013	0.758	-1.992	-0.472	-0.040	0.447	2.315

Table 3: The Effect of Management Quality Factor on Management Team Compensation

This table reports the OLS regression results of various executive compensation measures on management quality factor (*MQF*). For each firm-year, *Ln(Average Total Compensation)* is the natural logarithm of the amount of total compensation divided by the number of managers. *Ln(Average Cash Compensation)* is the natural logarithm of the amount of cash compensation divided by the number of managers. *Equity/Total Compensation* is defined as the fraction of equity compensation out of total compensation. Total compensation includes cash compensation and equity compensation. Cash compensation consists of base cash salary and bonus. Equity compensation consists of the value of shares awarded, value of LTIP awarded, and value of options awarded. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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)
Variable	Ln(Average Total Compensation)	Ln(Average Cash Compensation)	Equity/Total Compensation
MQF	0.063***	0.011	0.027***
	(0.015)	(0.011)	(0.004)
Ln(Assets)	0.472***	0.254***	0.064***
	(0.009)	(0.006)	(0.003)
M/B	0.478***	0.119***	0.090***
	(0.029)	(0.019)	(0.008)
ROA	-0.047	0.131**	-0.001
	(0.075)	(0.062)	(0.026)
CAPEX/Assets	0.049	-0.325**	0.051
	(0.210)	(0.153)	(0.059)
R&D/Assets	0.366***	0.001	0.079*
	(0.130)	(0.084)	(0.045)
Stock Return	0.150***	0.063***	0.018***
	(0.013)	(0.008)	(0.004)
HHI	1.035***	-0.613*	0.522***
	(0.393)	(0.336)	(0.162)
Average Tenure	-0.019***	0.005	-0.009***
	(0.005)	(0.004)	(0.002)
Observations	12,240	12,232	12,370
Adjusted R-squared	0.530	0.462	0.193
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 4: The Effect of Management Quality on R&D Expenditures

This table reports the OLS regression results of the ratio of R&D expenditures to total assets (*R&D/Assets*) on management quality factor (*MQF*). *R&D/Assets* is defined as research and development expenses divided by total assets; *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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)
Variable	R&D/Assets$_{t+1}$	R&D/Assets$_{t+2}$	R&D/Assets$_{t+3}$
MQF	0.008***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)
Ln(Assets)	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
M/B	0.057***	0.043***	0.039***
	(0.002)	(0.002)	(0.002)
ROA	-0.216***	-0.198***	-0.194***
	(0.010)	(0.010)	(0.010)
CAPEX/Assets	-0.052***	-0.052***	-0.047***
	(0.011)	(0.011)	(0.012)
Stock Return	-0.000	-0.006***	-0.004***
	(0.001)	(0.001)	(0.001)
HHI	0.029*	0.014	0.007
	(0.016)	(0.017)	(0.019)
Average Tenure	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Observations	27,688	23,741	19,887
Adjusted R-squared	0.559	0.493	0.472
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 5: The Effect of Management Quality on the Quantity and Quality of Corporate Innovation

This table reports the OLS regression results of quantity and quality of corporate innovation on management quality factor (*MQF*). Panels A, B, and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Three-Year Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed over the next three years; *Three-Year Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed over the next three years; *Three-Year Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent received by the firm's patents filed over the next three years. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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 Effect of MQF on the Number of Patents			
	(1)	(2)	(3)
Variable	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$
MQF	0.128***	0.129***	0.128***
	(0.011)	(0.012)	(0.013)
Ln(Assets)	0.146***	0.142***	0.138***
	(0.006)	(0.006)	(0.006)
M/B	0.113***	0.121***	0.122***
	(0.011)	(0.012)	(0.012)
ROA	-0.010	0.002	0.005
	(0.021)	(0.022)	(0.023)
CAPEX/Assets	-0.043	-0.021	-0.008
	(0.064)	(0.066)	(0.070)
R&D/Assets	0.234***	0.190***	0.157***
	(0.045)	(0.045)	(0.045)
Stock Return	-0.031***	-0.026***	-0.016***
	(0.005)	(0.005)	(0.005)
HHI	0.109	0.067	-0.026
	(0.183)	(0.191)	(0.182)
Average Tenure	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
Observations	27,688	24,519	21,250
Adjusted R-squared	0.390	0.384	0.375
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B: The Effect of MQF on the Total Number of Citations			
	(1)	(2)	(3)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$
MQF	0.016***	0.016***	0.016***
	(0.002)	(0.002)	(0.002)
Ln(Assets)	0.018***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)
M/B	0.013***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)
ROA	-0.010***	-0.010***	-0.008**
	(0.003)	(0.003)	(0.003)
CAPEX/Assets	-0.006	-0.007	-0.009
	(0.010)	(0.010)	(0.010)
R&D/Assets	-0.000	-0.005	-0.005
	(0.006)	(0.006)	(0.006)
Stock Return	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
HHI	-0.021	-0.034	-0.035
	(0.032)	(0.033)	(0.031)
Average Tenure	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Observations	27,688	24,519	21,250
Adjusted R-squared	0.256	0.251	0.241
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel C: The Effect of MQF on the Citations per Patent			
	(1)	(2)	(3)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$
MQF	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Ln(Assets)	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
M/B	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)
ROA	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
CAPEX/Assets	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.001)
R&D/Assets	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)
Stock Return	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)
HHI	-0.005**	-0.005**	-0.004
	(0.002)	(0.002)	(0.002)
Average Tenure	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Observations	27,688	24,519	21,250
Adjusted R-squared	0.140	0.139	0.136
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 6: The Effect of Individual Management Quality Measures on Corporate Innovation

This table reports the OLS regression results of corporate innovation on individual management quality factor variables. Panels A, B, and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Team Size* is the number of managers (VP or higher) in a firm's management team; *MBA* is the fraction of the managers that have MBA degrees; *PhD* is the fraction of the managers that have PhD degrees; *Prior Work Experience* is the fraction of top managers that have experience working as VP or higher in other companies; *Prior Board Experience* is the average number of board positions that each manager has served on; *Employment Connections* is the average number of connections that each manager has through prior employment (if two managers worked in the same previous company during overlapping time periods, either as managers or directors, those two are defined as connected); *Education Connections* is the average number of graduate connections that each manager has through education (if two managers graduate from the same university with the same degree within one year of each other, those two are defined as connected). Control variables are the same as in Table 5 in all regressions and coefficient estimates on controls are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. Coefficients and standard errors in Panel C are multiplied by 100. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: The Effect of Individual Management Quality Measures on the Number of Patents

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Team Size	0.029***						
	(0.003)						
MBA		0.120***					
		(0.033)					
PhD			0.356***				
			(0.057)				
Prior Work Experience				0.035			
				(0.035)			
Prior Board Experience					-0.002		
					(0.026)		
Employment Connections						0.013***	
						(0.001)	
Education Connections							0.012***
							(0.002)
Observations	27,688	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.389	0.370	0.374	0.369	0.369	0.391	0.372
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: The Effect of Individual Management Quality Measures on the Total Number of Citations							
Variable	(1)	(2)	(7)	(3)	(6)	(5)	(4)
Team Size	0.004***						
	(0.000)						
MBA		0.013***					
		(0.005)					
PhD			0.021***				
			(0.007)				
Prior Work Experience				-0.006			
				(0.005)			
Prior Board Experience					-0.002		
					(0.003)		
Employment Connections						0.002***	
						(0.000)	
Education Connections							0.001***
							(0.000)
Observations	27,688	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.261	0.240	0.240	0.239	0.239	0.259	0.242
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: The Effect of Individual Management Quality Measures on the Number of Citations per Patent							
Variable	(1)	(2)	(7)	(3)	(6)	(5)	(4)
Team Size	0.013***						
	(0.002)						
MBA		0.059**					
		(0.027)					
PhD			0.112***				
			(0.042)				
Prior Work Experience				-0.004			
				(0.028)			
Prior Board Experience					-0.024		
					(0.018)		
Employment Connections						0.005***	
						(0.001)	
Education Connections							0.005***
							(0.002)
Observations	27,688	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.140	0.136	0.136	0.135	0.135	0.139	0.136
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: The Effect of Management Quality on Corporate Innovation: Instrumental Variable Analysis

This table reports the IV regression results of corporate innovation on management quality factor (*MQF*). The instrumental variables we use is described in Section 3.4.3. Column (1) of Panel A reports the first-stage result, i.e., regressing *MQF* on the instrument and other controls. Columns (2)-(4) of Panel A report the second-stage results of the IV regressions using a firm's number of patents applied in a given year as dependent variables. Panels B and C report second-stage results using the total number of citations and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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: First and Second-Stage Results of the Number of Patents on MQF				
	(1)	(2)	(3)	(4)
Variable	MQF	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$
Instrument	0.002***			
	(0.000)			
MQF		0.627***	0.414***	0.239
		(0.147)	(0.139)	(0.161)
Acquisitions(t-5)	0.010***	0.000	0.001**	0.002**
	(0.001)	(0.000)	(0.000)	(0.001)
Ln(Assets)	0.069***	0.110***	0.121***	0.128***
	(0.008)	(0.012)	(0.010)	(0.011)
M/B	0.167***	0.028	0.067**	0.097***
	(0.017)	(0.028)	(0.026)	(0.031)
ROA	-0.195***	0.082**	0.055	0.021
	(0.032)	(0.037)	(0.034)	(0.035)
CAPEX/Assets	-0.729***	0.337**	0.191	0.089
	(0.095)	(0.135)	(0.121)	(0.124)
R&D/Assets	0.213***	0.048	0.072	0.072
	(0.058)	(0.059)	(0.052)	(0.051)
Stock Return	-0.049***	-0.005	-0.010	-0.010
	(0.007)	(0.009)	(0.009)	(0.009)
Average Tenure	-0.036***	0.021***	0.013**	0.006
	(0.003)	(0.006)	(0.005)	(0.006)
HHI	-0.104	0.232	0.208	0.155
	(0.274)	(0.243)	(0.226)	(0.197)
Observations	25,945	25,945	23,096	20,119
Adjusted R Squared	0.107			
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Panel B: Second-Stage Results of Total Number of Citations on MQF			
	(1)	(2)	(3)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$
MQF	0.083***	0.058**	0.057**
	(0.021)	(0.024)	(0.028)
Acquisitions(t-5)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Ln(Assets)	0.013***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)
M/B	0.001	0.006	0.005
	(0.004)	(0.004)	(0.005)
ROA	0.003	-0.001	-0.001
	(0.005)	(0.005)	(0.006)
CAPEX/Assets	0.046**	0.024	0.022
	(0.019)	(0.019)	(0.021)
R&D/Assets	-0.018**	-0.016**	-0.016**
	(0.008)	(0.007)	(0.008)
Stock Return	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.002)
Average Tenure	0.003***	0.002**	0.002*
	(0.001)	(0.001)	(0.001)
HHI	0.001	-0.008	-0.001
	(0.039)	(0.038)	(0.035)
Observations	25,945	23,096	20,119
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Panel C: Second-Stage Results of Citations per Patent on MQF			
	(1)	(2)	(3)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$
MQF	0.004**	0.004**	0.001
	(0.002)	(0.002)	(0.002)
Acquisitions(t-5)	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Ln(Assets)	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)
M/B	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
ROA	0.001	0.000	-0.000
	(0.000)	(0.000)	(0.000)
CAPEX/Assets	0.002	0.002	-0.000
	(0.001)	(0.001)	(0.002)
R&D/Assets	-0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)
Stock Return	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Average Tenure	0.000**	0.000*	0.000
	(0.000)	(0.000)	(0.000)
HHI	-0.004	-0.003	-0.002
	(0.002)	(0.003)	(0.002)
Observations	25,945	23,096	20,119
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Table 8: The Effect of Management Quality on Corporate Innovative Efficiency

This table reports the OLS regression results of innovative efficiency on management quality factor (*MQF*). Panels A and B report OLS and Instrumental Variable regression results, respectively. Innovative efficiency is measured by *Patents/R&D* and *Citations/R&D*. *Patents/R&D* is defined as the natural logarithm of one plus the ratio of firm's truncation-adjusted number of patents applied in a given year scaled by its R&D capital (the five-year cumulative R&D expenses assuming an annual depreciation rate of 20%); i.e., $Patents/R\&D_{i,t} = \ln(1+\frac{Patent\ count_{i,t}}{R\&D_{i,t}+0.8*R\&D_{i,t-1}+0.6*R\&D_{i,t-2}+0.4*R\&D_{i,t-3}+0.2*R\&D_{i,t-4}})$. *Citations/R&D* is defined as the natural logarithm of one plus the ratio of firm's total adjusted number of citations applied in year *t* scaled by its R&D capital, i.e., $Citations/R\&D_{i,t} = \ln(1+\frac{Total\ number\ of\ citations_{i,t}}{R\&D_{i,t}+0.8*R\&D_{i,t-1}+0.6*R\&D_{i,t-2}+0.4*R\&D_{i,t-3}+0.2*R\&D_{i,t-4}})$. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. Coefficients and standard errors in Columns (4)-(6) are multiplied by 100. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Patents/R&D$_{t+1}$	Patents/R&D$_{t+2}$	Patents/R&D$_{t+3}$	Citations/R&D$_{t+1}$	Citations/R&D$_{t+2}$	Citations/R&D$_{t+3}$
MQF	0.002**	0.002***	0.002***	0.008**	0.007**	0.008**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Ln(Assets)	-0.001**	-0.001**	-0.001	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
M/B	0.002**	0.001	0.000	0.009*	0.008*	0.006
	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.004)
ROA	0.005***	0.005**	0.004**	0.013	0.012	0.009
	(0.002)	(0.002)	(0.002)	(0.009)	(0.009)	(0.010)
CAPEX/Assets	0.025***	0.020***	0.015**	0.096**	0.039	0.020
	(0.006)	(0.007)	(0.007)	(0.038)	(0.037)	(0.033)
Stock Return	-0.000	0.000	-0.000	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.000)	(0.003)	(0.003)	(0.003)
HHI	-0.106**	-0.171***	-0.224***	-0.885***	-1.232***	-1.374**
	(0.041)	(0.044)	(0.065)	(0.322)	(0.420)	(0.591)
Average Tenure	0.000*	0.000*	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	15,998	14,235	12,378	15,998	14,235	12,378
Adjusted R-squared	0.118	0.120	0.113	0.087	0.090	0.083
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: The Effect of Management Quality on Corporate Innovation: Interaction Tests

This table reports the main regression results interacted with relevant variables. Columns (1)-(3) summarize the regression results with *MQF* interacted with industry financial constraints, using the number of patents, the total number of citations, and the number of citations per patent for a firm in a given year as dependent variables, respectively. *Constrained* is a dummy variable, which is equal to one if the value of external finance dependence is larger than zero and zero otherwise. External finance dependence for an industry (defined at 2-digit SIC level) in a given year is defined by the method outlined in Rajan and Zingales (1998). Columns (4)-(6) summarize regression results with management quality factor (*MQF*) interacted with industry Herfindahl-Hirschman Index (*HHI*), using the number of patents, the total number of citations, and the number of citations per patent for a firm in a given year as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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)
Variable	$Ln(Patents)_{t+1}$	$Ln(Citations)_{t+1}$	$Ln(Citations/Patent)_{t+1}$	$Ln(Patents)_{t+1}$	$Ln(Citations)_{t+1}$	$Ln(Citations/Patent)_{t+1}$
MQF	0.105***	0.013***	0.001***	0.174***	0.021***	0.001***
	(0.012)	(0.002)	(0.000)	(0.015)	(0.002)	(0.000)
MQF×Constrained	0.077***	0.010***	-0.000			
	(0.021)	(0.003)	(0.000)			
Constrained	0.011	-0.005***	-0.000***			
	(0.011)	(0.002)	(0.000)			
MQF×HHI				-0.775***	-0.078***	-0.002*
				(0.140)	(0.022)	(0.001)
HHI	0.127	-0.011	-0.005**	0.128	-0.019	-0.005**
	(0.184)	(0.033)	(0.002)	(0.179)	(0.032)	(0.002)
Ln(Assets)	0.147***	0.018***	0.001***	0.146***	0.018***	0.001***
	(0.006)	(0.001)	(0.000)	(0.006)	(0.001)	(0.000)
M/B	0.111***	0.012***	0.000***	0.111***	0.012***	0.000***
	(0.011)	(0.002)	(0.000)	(0.011)	(0.002)	(0.000)
ROA	-0.008	-0.011***	-0.000	-0.010	-0.010***	-0.000
	(0.021)	(0.003)	(0.000)	(0.021)	(0.003)	(0.000)
CAPEX/Assets	-0.035	-0.004	-0.000	-0.042	-0.006	-0.000
	(0.063)	(0.010)	(0.000)	(0.065)	(0.010)	(0.000)
R&D/Assets	0.228***	-0.001	0.001**	0.226***	-0.001	0.001**
	(0.045)	(0.006)	(0.000)	(0.045)	(0.006)	(0.000)
Stock Return	-0.031***	-0.003***	-0.000**	-0.031***	-0.003***	-0.000*
	(0.005)	(0.001)	(0.000)	(0.005)	(0.001)	(0.000)
Average Tenure	0.001	0.000	0.000	0.001	0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Observations	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.392	0.258	0.140	0.393	0.257	0.140
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: The Effect of Management Quality on the Net Inflow of Inventors

This table reports the OLS regression results of the net inflow of inventors for a firm in a given year on management quality factor (*MQF*). For any inventor that filed patents in different firms or organizations, we assume a move occurred in the year when he filed the first patent in that firm. For a firm, the inventor's move-in year and move-out year are the year when the inventor filed the first patent in this firm and the year when he filed the first patent in the subsequent firm. The inflow and outflow of inventors are defined as the natural logarithm of one plus the total number of inventors that move in and that move out aggregated at the firm-year level. *Net Inflow* is defined as the difference between the inflow and outflow of inventors as measured above. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, 2-digit SIC industry fixed effects, and state fixed effects are included in all regressions. All standard errors are adjusted for clustering 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)
Variable	Net Inflow$_{t+1}$	Net Inflow$_{t+2}$	Net Inflow$_{t+3}$
MQF	0.050***	0.049***	0.054***
	(0.007)	(0.007)	(0.007)
Ln(Assets)	0.073***	0.067***	0.060***
	(0.003)	(0.003)	(0.003)
M/B	0.076***	0.080***	0.076***
	(0.008)	(0.008)	(0.008)
ROA	0.051***	0.053***	0.050***
	(0.016)	(0.015)	(0.016)
CAPEX/Assets	0.123**	0.104**	0.070
	(0.050)	(0.048)	(0.050)
R&D/Assets	0.356***	0.257***	0.196***
	(0.039)	(0.035)	(0.036)
Stock Return	-0.025***	-0.016***	-0.007*
	(0.005)	(0.004)	(0.004)
HHI	0.344**	0.273*	0.136
	(0.146)	(0.140)	(0.156)
Average Tenure	-0.004***	-0.003***	-0.002*
	(0.001)	(0.001)	(0.001)
Observations	25,945	23,096	20,119
Adjusted R-squared	0.255	0.244	0.234
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Table 11: The Effect of Management Quality on the Net Inflow of High Quality and Low Quality Inventors

This table reports the OLS regression results of the net inflow of high-quality and net inflow of low-quality inventors for a firm in a given year on management quality factor (*MQF*) and tests the statistical difference of coefficient estimates. Panel A reports the effect of *MQF* on the net inflow of high-quality inventors and the net inflow of low-quality inventors. *Net Inflow of High* is the difference between the natural logarithm of one plus the number of high-quality inventors that move into the firm and the natural logarithm of one plus the number of high-quality inventors that move out of the firm in a given year; *Net Inflow of Low* is the difference between the natural logarithm of one plus the number of low-quality inventors that move into the firm and the natural logarithm of one plus the number of low-quality inventors that move out of the firm in a given year. Inventor quality is measured by the number of citations scaled by total number of patents that he has filed prior to the current year. An inventor is considered as a high-quality inventor if his prior track record of citations per patent is above the sample median. Otherwise, an inventor is considered as a low-quality inventor. Panel B reports the difference between the coefficient estimates using *Net Inflow of High* and *Net Inflow of Low* as dependent variables and tests their statistical differences. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, 2-digit SIC industry fixed effects, and state fixed effects are included in all regressions. All standard errors are adjusted for clustering 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: Net inflow of High-Quality and Low-Quality Inventors (OLS)

Variable	(1) Net Inflow of $High_{t+1}$	(2) Net Inflow of Low_{t+1}	(3) Net Inflow of $High_{t+2}$	(4) Net Inflow of Low_{t+2}	(5) Net Inflow of $High_{t+3}$	(6) Net Inflow of Low_{t+3}
MQF	0.054***	0.004***	0.053***	0.004***	0.056***	0.004***
	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)
Ln(Assets)	0.078***	0.004***	0.071***	0.004***	0.064***	0.003***
	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)
M/B	0.079***	0.002***	0.084***	0.003***	0.080***	0.003***
	(0.009)	(0.001)	(0.009)	(0.001)	(0.008)	(0.001)
ROA	0.050***	0.001	0.053***	0.001	0.051***	0.002*
	(0.016)	(0.001)	(0.016)	(0.001)	(0.016)	(0.001)
CAPEX/Assets	0.123**	0.004	0.112**	0.003	0.082	-0.003
	(0.051)	(0.004)	(0.050)	(0.004)	(0.051)	(0.004)
R&D/Assets	0.356***	0.013***	0.264***	0.008***	0.206***	0.008**
	(0.040)	(0.004)	(0.036)	(0.003)	(0.038)	(0.003)
Stock Return	-0.025***	-0.001**	-0.018***	-0.000	-0.008*	-0.001**
	(0.005)	(0.000)	(0.005)	(0.000)	(0.004)	(0.000)
HHI	0.393***	-0.001	0.313**	0.001	0.161	0.001
	(0.151)	(0.011)	(0.145)	(0.010)	(0.162)	(0.010)
Average Tenure	-0.004***	0.000	-0.003***	0.000	-0.002*	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	25,945	25,945	23,096	23,096	20,119	20,119
Adjusted R-squared	0.263	0.063	0.253	0.061	0.241	0.060
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Difference between Net Inflow of High Quality and Low Quality Inventors (OLS)

	$Difference_{t+1}$	$Difference_{t+2}$	$Difference_{t+3}$
Difference	0.050***	0.049***	0.052***

Table 12: The Effect of the Net Inflow of High Quality Inventors on Corporate Innovation

This table reports the OLS regression results of corporate innovation on the net inflow of high quality inventors and management quality factor (*MQF*). Panels A, B and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Net Inflow of High* is the difference between the natural logarithm of one plus the number of high-quality inventors that move into the firm and the natural logarithm of one plus the number of high-quality inventors that move out of the firm in a given year. Control variables are the same as in Table 5 in all regressions and results are not reported to save space. Constant, year fixed effects, 2-digit SIC industry fixed effects, and state fixed effects are included in all regressions. All standard errors are adjusted for clustering 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: MQF, Net Inflow of High Quality Inventors, and the Number of Patents			
	(1)	(2)	(3)
Variable	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$
Net Inflow of High	0.572***	0.526***	0.466***
	(0.013)	(0.014)	(0.014)
MQF	0.096***	0.093***	0.090***
	(0.008)	(0.009)	(0.010)
Observations	25,945	23,096	20,119
Adjusted R-squared	0.578	0.559	0.528
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Panel B: MQF, Net Inflow of High Quality Inventors, and the Total Number of Citations			
	(1)	(2)	(3)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$
Net Inflow of High	0.063***	0.058***	0.051***
	(0.003)	(0.003)	(0.003)
MQF	0.014***	0.013***	0.013***
	(0.001)	(0.002)	(0.002)
Observations	25,945	23,096	20,119
Adjusted R-squared	0.372	0.360	0.334
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Panel C: MQF, Net Inflow of High Quality Inventors, and the Number of Citations per Patent			
	(1)	(2)	(3)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$
Net Inflow of High	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
MQF	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Control Variables	Yes	Yes	Yes
Observations	25,945	23,096	20,119
Adjusted R-squared	0.181	0.184	0.184
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Table 13: The Effect of Management Quality on Net Change in the Average Quality of Inventors

This table reports the OLS regression results of the change in the average quality of inventors for a firm in a given year on management quality factor (*MQF*). *Incoming Quality* is the natural logarithm of one plus the average quality of all the inventors that move into the firm in a given year. *Outgoing Quality* is natural logarithm of one plus the average quality of all the inventors that move out of the firm in a given year. *Net Quality Change* is defined as the difference between *Incoming Quality* and *Outgoing Quality*. Inventor quality is measured by the number of citations scaled by total number of patents that he has filed prior to the current year. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index; and *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, 2-digit SIC industry fixed effects, and state fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. Coefficients and standard errors are multiplied by 100. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)
Variable	Net Quality Change$_{t+1}$	Net Quality Change$_{t+2}$	Net Quality Change$_{t+3}$
MQF	0.017***	0.016***	0.021***
	(0.006)	(0.005)	(0.005)
Ln(Assets)	0.030***	0.027***	0.024***
	(0.002)	(0.002)	(0.002)
M/B	0.025***	0.025***	0.024***
	(0.006)	(0.006)	(0.006)
ROA	0.010	0.007	0.012
	(0.013)	(0.013)	(0.013)
CAPEX/Assets	0.074**	0.086**	0.034
	(0.037)	(0.039)	(0.039)
R&D/Assets	0.102***	0.056**	0.038
	(0.031)	(0.027)	(0.028)
Stock Return	-0.008*	-0.001	-0.002
	(0.004)	(0.004)	(0.004)
HHI	-0.204	-0.161	-0.101
	(0.156)	(0.144)	(0.148)
Average Tenure	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Observations	25,945	23,096	20,119
Adjusted R-squared	0.087	0.083	0.079
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Table 14: The Effect of Management Quality on Highly Successful, Unsuccessful, and Moderately Successful Innovations

This table reports OLS regression results of the number of very successful, unsuccessful and moderately successful patents on management quality factor (*MQF*). Panels A, B, and C correspond to the regression results with dependent variables that are one, two and three years ahead, respectively. *Top 10%* is the natural logarithm of one plus the firm's number of patents that received cites within the top 10% among all patents in the same 3-digit patent class and application year; *No Cites* is the natural logarithm of one plus the number of patents that received no citation; *Moderate Cites* is the natural logarithm of one plus the number of patents that received at least one citation but below the top 10% among all patents. Columns (1)-(3) report the regression coefficients using *Top 10%*, *No Cites* and *Moderate Cites* as dependent variables, respectively; Columns (4)-(6) report and test the significance of difference between any two of the coefficient estimates in Columns (1)-(3). Control variables are the same as in Table 5 in all regressions and results are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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 Effect of MQF on One-year-ahead patenting						
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Top 10%$_{t+1}$	No Cites$_{t+1}$	Moderate Cites$_{t+1}$	Dif (1)-(2)	Dif (1)-(3)	Dif (2)-(3)
MQF	0.338***	0.146***	0.134***	0.192***	0.204***	0.012**
	(0.027)	(0.012)	(0.014)	(0.016)	(0.016)	(0.005)
Observations	27,688	27,688	27,688			
Adjusted R-squared	0.417	0.359	0.378			
Control Variables	Yes	Yes	Yes			
Industry FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			
Panel B: The Effect of MQF on Two-year-ahead patenting						
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Top 10%$_{t+2}$	No Cites$_{t+2}$	Moderate Cites$_{t+2}$	Dif (1)-(2)	Dif (1)-(3)	Dif (2)-(3)
MQF	0.335***	0.148***	0.130***	0.187***	0.205***	0.018***
	(0.029)	(0.013)	(0.014)	(0.017)	(0.017)	(0.006)
Observations	24,519	24,519	24,519			
Adjusted R-squared	0.409	0.357	0.369			
Control Variables	Yes	Yes	Yes			
Industry FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			
Panel C: The Effect of MQF on three-year-ahead patenting						
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Top 10%$_{t+3}$	No Cites$_{t+3}$	Moderate Cites$_{t+3}$	Dif (1)-(2)	Dif (1)-(3)	Dif (2)-(3)
MQF	0.332***	0.146***	0.126***	0.186***	0.206***	0.020***
	(0.031)	(0.014)	(0.015)	(0.018)	(0.019)	(0.006)
Observations	21,250	21,250	21,250			
Adjusted R-squared	0.400	0.354	0.355			
Control Variables	Yes	Yes	Yes			
Industry FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			

Internet Appendix (Not to Be Published)

Table A1: Robustness Test: The Effect of Management Quality on Corporate Innovation for Innovative Firms Only

This table reports the OLS regression results of corporate innovation on management quality factor (*MQF*) using innovative firms only. Innovative firms are defined as firms that have filed at least one patent application over the sample period of 1999-2009. Panels A, B, and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. Control variables are the same as in Table 5 in all regressions and results are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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 Effect of MQF on the Number of Patents			
	(1)	(2)	(3)
Variable	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$
MQF	0.134***	0.138***	0.136***
	(0.016)	(0.017)	(0.017)
Observations	15,251	13,742	12,118
Adjusted R-squared	0.426	0.423	0.416
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel B: The Effect of MQF on the Total Number of Citations			
	(1)	(2)	(3)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$
MQF	0.018***	0.018***	0.018***
	(0.003)	(0.003)	(0.003)
Observations	15,251	13,742	12,118
Adjusted R-squared	0.292	0.286	0.274
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel C: The Effect of MQF on the Number of Citations per Patent			
	(1)	(2)	(3)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$
MQF	0.000***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Observations	15,251	13,742	12,118
Adjusted R-squared	0.110	0.113	0.113
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table A2: Robustness Test: MQF without Team Size

This table reports the OLS regression results for corporate innovation with management quality factor without team size (*MQF-No Team Size*) as the key independent variable. *MQF-No Team Size* is defined in the same way as *MQF* except that we exclude team size in the common factor analysis. Panels A, B, and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. Control variables are the same as in Table 5 in all regressions and results are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering 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 Effect of MQF-No Team Size on the Number of Patents			
	(1)	(2)	(3)
Variable	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$
MQF-No Team Size	0.083***	0.077***	0.068***
	(0.011)	(0.011)	(0.012)
Observations	27,688	24,519	21,250
Adjusted R-squared	0.375	0.368	0.359
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel B: The Effect of MQF-No Team Size on the Total Number of Citations			
	(1)	(2)	(3)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$
MQF-No Team Size	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)
Observations	27,688	24,519	21,250
Adjusted R-squared	0.242	0.237	0.227
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel C: The Effect of MQF-No Team Size on the Number of Citations per Patent			
	(1)	(2)	(3)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$
MQF-No Team Size	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Observations	27,688	24,519	21,250
Adjusted R-squared	0.136	0.135	0.131
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table A3: Robustness Test: Controlling for Industry×Year×State Fixed Effects

This table replicates the baseline regression results of corporate innovation on management quality factor (*MQF*) as in Table 5 controlling for industry×year×state fixed effects. Panel A, B, and C report the OLS regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus a firm's total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. Control variables are the same as in Table 5 in all regressions and results are not reported to save space. Constant and industry×year×state fixed effects are included in all regressions. All standard errors are adjusted for clustering 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 Effect of MQF on the Number of Patents			
	(1)	(2)	(3)
Variable	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$
MQF	0.158***	0.158***	0.157***
	(0.015)	(0.016)	(0.016)
Observations	25,945	23,096	20,119
Adjusted R-squared	0.370	0.365	0.351
Control Variables	Yes	Yes	Yes
Industry×Year×State FE	Yes	Yes	Yes
Panel B: The Effect of MQF on the Total Number of Citations			
	(1)	(2)	(3)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$
MQF	0.020***	0.019***	0.019***
	(0.002)	(0.002)	(0.003)
Observations	25,945	23,096	20,119
Adjusted R-squared	0.237	0.232	0.217
Control Variables	Yes	Yes	Yes
Industry×Year×State FE	Yes	Yes	Yes
Panel C: The Effect of MQF on the Number of Citations per Patent			
	(1)	(2)	(3)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$
MQF	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Observations	25,945	23,096	20,119
Adjusted R-squared	0.153	0.144	0.133
Control Variables	Yes	Yes	Yes
Industry×Year×State FE	Yes	Yes	Yes