Title
Essays on Finance and Corporate Innovation

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Publication Date
2018

Peer reviewed|Thesis/dissertation

Essays on Finance and Corporate Innovation

by

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A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:
Professor Adair Morse, Chair
Professor Gustavo Manso
Professor Ulrike Malmendier
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Fall 2018

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Abstract

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This dissertation studies the complex interrelationship between finance and corporate innovation policy. In the first two chapters, I consider the real impact that financial structures and corporate governance can have on firm technological innovation. First, I use property rights theory to highlight how alternative financial contracting structures differ in their ability to nurture the innovative activities of their investee firms. Second, I examine how the firm's choice of Chief Executive Officer (CEO), specifically the firm's choice to install a firm founder or a non-firm founder ("professional") as CEO, can impact interrelated dimensions of corporate policy and ultimately firm value. In the final chapter, I study the stock market consequences of corporate technological innovation. Specifically, I evaluate the ability of equity analysts and public market investors to identify and value a firm's innovation search strategy, characterized as a choice between the exploration of new technological capabilities and the exploitation of a firm's existing technological competencies.

In **Chapter 1**, **Financial Contracting for Innovation: Property Rights in Action**, I study the relative ability of three financial contracting structures - namely independent venture capital (IVC), corporate venture capital (CVC) and strategic alliances - to promote entrepreneurial firm innovation. In property rights theory, financial contracting structures can align property rights to promote start-up firm innovation. I first provide novel estimates that strategic alliances have 6% to 11% higher overall innovative success rates compared to corporate venture capital and independent venture capital, respectively. Then, using a matched quasi-experiment in clinical trials to decompose selection (endogenous matching) and treatment effects, I find that strategic alliances promote 5% higher overall innovative success rates than both CVC and IVC (33% change in relative terms). I map the underpinnings of alliance success to the mechanisms of knowledge sharing and willingness to support costly experimentation.

In **Chapter 2**, **'Til Death Do Us Part: The Relative Merits of Founder CEOs**, I address a question faced by every firm in the economy, namely is it optimal for a firm's founder to lead the company as CEO? To identify the treatment effect of founder CEOs on corporate policy and firm value, I exploit a natural experiment involving exogenous founder-to-professional CEO turnovers that arise from a founder's death or illness. I find that, relative to comparable firms that retain their founder CEO, firms that must switch to a professional CEO experience a 10%

reduction in their internally generated innovation. However, professional CEOs counteract this reduced internal R&D productivity by acquiring external technologies through greater M&A activity, increasing firm leverage and nurturing larger, more stable top management teams. These combined policy changes appear to have offsetting firm value implications, implying a "horses for courses" approach to choosing between a founder CEO and a professional CEO.

In **Chapter 3**, **Innovation Search Strategy and Predictable Returns** *(with Benjamin Balsmeier, Lee Fleming and Gustavo Manso)*, we hypothesize that because of the intangible and highly uncertain nature of innovation, investors may have difficulty processing information associated with a firm's innovation and innovation search strategy. Due to cognitive and strategic biases, investors are likely to pay more attention to unfamiliar explorative patents rather than incremental exploitative patents. We find that firms focusing on exploitation rather than exploration tend to generate superior subsequent short-term operating performance. Analysts do not seem to detect this, as firms currently focused on exploitation tend to outperform the market's near-term earnings expectations. The stock market also seems unable to accurately incorporate information about a firm's innovation search strategy. We find that firms with exploitation strategies are undervalued relative to firms with exploration strategies and that this return differential is incremental to standard risk and innovation-based pricing factors examined in the prior literature. This result suggests a more nuanced view on whether stock market pressure hampers innovation, and may have implications for optimal firm financing choices and corporate disclosure policy.

Acknowledgements

There are many people whom I would like to thank for their time and assistance in the construction of this dissertation and, more generally, for helping me navigate my PhD.

First, I would like to thank my dissertation chair, Adair Morse, who has provided unrivalled insight into the world of corporate finance and who has devoted so much time and effort into making me a better scholar. Your continued dedication to academic excellence is truly inspiring and I know that I would not be where I am today without your guidance.

Second, I would also like to say a very special thank you to those who have offered their valuable time and input into my research, particularly Gustavo Manso, Ulrike Malmendier and Lee Fleming. Your seminal work in the innovation and corporate finance literature has greatly shaped my own research interests and I am fortunate to have had the benefit of your collective wisdom and encouragement as members of my dissertation committee.

Third, I am grateful for the support of the faculty and staff at the Haas Business School. Your generosity is very much appreciated and I hope that future PhD students can receive the same opportunities that have been graciously afforded to me.

Fourth, I would like to thank the entire Finance and Economics PhD cohort for a memorable and very rewarding experience. I am sure that many life-long friendships have been forged over the course of this year and I wish everyone the best of luck in their future endeavors.

Last but certainly not least, I would like to thank my amazing wife Daisy, my beautiful boys Hayden and Lachlan as well as my entire family (particularly my parents and big sister Larissa) for their support and understanding throughout my PhD. Your continued love and encouragement has been a great source of motivation for which I cannot thank you enough.

Chapter 1:
Financial contracting for innovation: Property rights in action

1.1 INTRODUCTION

Two widely accepted economic principles are that technological innovation is a key driver of the real economy (Stiglitz & Greenwald, 2015; Schumpeter, 1942) and financial intermediaries are vital for economic growth (Levine, 2005; Rajan & Zingales, 2003). However, there remains considerable debate about the fundamental drivers of technological innovation and the role of financial contracting in nurturing firm innovation (Seru, 2014; Kerr, Lerner & Schoar, 2014).

In this paper, I study the relative ability of three financial contracting structures - independent venture capital (IVC), corporate venture capital (CVC) and strategic alliances - to promote entrepreneurial firm innovation. While there is literature on the role of these financing structures in isolation (IVC: Hellmann & Puri (2002), Sorensen (2007), Bernstein, Giroud & Townsend (2016); CVC: Ma (2016), Basu, Phelps & Kotha, (2011)),[1] much less is known about the relative innovation outcomes of portfolio firms across these different structures and the economic drivers of these differences. One exception is the comparison of the innovative performance of IVC- versus CVC-backed firms, with the consensus view being that CVC-backed firms generate significantly more patents relative to IVC-backed firms post-investment (Chemmanur, Loutskina & Tian, 2014, and Alvarez-Garrido & Dushnitsky, 2016 c.f. Pahnke, Katila & Eisenhardt, 2015).

As motivation for my research, I observe significant differences in the percentage of drug development start-ups that obtain approval to market their drugs: 22% for alliance-backed firms, 16% for CVC-backed firms and 11% for IVC-backed firms. This observation raises important questions: What fundamental factors lead firms to choose IVC, CVC and alliance relationships? How much of the total effect is attributable to selection (endogenous matching) versus treatment (knowledge sharing/entrepreneur-financier interaction)? What mechanisms explain any treatment effects? To answer these questions, my research advances the prior literature in two key respects.

First, I use the property rights and theory of the firm arguments of Hart & Moore (1990) and Rajan & Zingales (1998) to consider the effect of both the type of financial intermediary *and* the form of entrepreneur-financier interaction on start-up firm innovation. IVC, CVC and strategic alliances differ in their allocation of cash flow and control rights to strategic corporate investors. This leads to large differences in their degree of engagement with the valuable intellectual property and resources of corporate investors (Ozmel, Robinson & Stuart, 2013). Importantly, because my unique comparison of strategic alliance and CVC investments by the *same* corporate investor allows me to hold the identity of the individual corporate investor fixed, I am able to directly consider how differences in the payoff and control structure of alliance and VC contracts impacts post-investment entrepreneur-financier relations and portfolio firm innovation.

Second, by using a matched quasi-experimental design involving clinical trials in the U.S. drug development industry, I disentangle how much of the observed difference in innovative outcomes across financing structures is due to treatment (some structures directly affect firm innovation) versus selection (two-sided matching and sorting on quality). My research design is plausibly a quasi-experiment because of three unique features of clinical trials. First, I identify a sample of early stage IVC-, CVC- and alliance-backed start-ups that are plausibly level on

[1] While Li, Qui & Wang (2015) and Chemmanur, Shen & Xie (2016) provide important evidence on the relationship between strategic alliances and firm innovation, both studies focus on publicly traded firms.

intrinsic quality. By only comparing the innovative outcomes of start-ups that reached Phase 2 clinical trials, I exploit the high threshold in terms of scientific proof (under 40% of early stage drug candidates reach Phase 2 trials per Paul, Mytelka, Dunwiddie, Persinger, Munos & Schacht, 2010) and cost (approximately US$50-130 million over 5+ years) that firms and their investors must meet in order to test a new drug candidate in Phase 2 clinical trials. Second, as discussed in Section 1.2, the treatment effect of financing structure in my setting will be concentrated after Phase 2 trials commence. Third, to the degree that arguments violating the mean conditional independence assumption still exist, I use insights from Matthews (2006) and Chatterji & Fabrizio (2012) to match firms on three fundamental factors driving financing choice: the expected benefit of access to financiers' technical resources, the possible benefit of leveraging a financier's commercialization experience and the potential cost of knowledge leakages to financiers. Thus, by limiting my main estimation sample to only the highest quality firms - those that progressed drug candidates through pre-clinical and Phase 1 trials to reach Phase 2 clinical trials ("Phase 2+" firms) - and only comparing firms with similar fundamental characteristics, it is "as if" financing structure has been randomly assigned across firms in this common support.

I present evidence unique to my setting that start-ups who reach Phase 2 trials have similar intrinsic quality. First, the quantity and quality of patents produced by Phase 2+ IVC-, CVC- and alliance-backed firms pre-investment is similar across financing structures. Second, the scientific output of start-up firm founders is comparable across Phase 2+ firms prior to the receipt of IVC or corporate funding, as indicated by the similarity in the patents and the total amount of peer-reviewed National Institute of Health (NIH) research grants awarded to firm founders. Finally, individual drug assessments undertaken by the U.S. pharmaceuticals regulator, the Food & Drugs Administration (FDA), indicate that Phase 2+ IVC-, CVC- and alliance-backed firms have drug candidates with an inherently similar level of chemical and therapeutic potential.

Embedded in my design is an increased understanding of the fundamental factors influencing the selection of start-up firms and financiers into IVC, CVC and alliance contracts. I find that the rising allocation of property rights to corporate investors under IVC, CVC & alliance contracts are used to balance the potential benefits of access to the technical and commercialization resources of corporate investors against the potential cost of reduced intellectual property value.

My results lead to three contributions. My first contribution is that, *without* applying my matched quasi-experiment, alliance-backed firms are more innovative (based on drug approvals and patents) than CVC-backed firms who in turn are more innovative than IVC-backed firms. This result provides novel evidence on the overlooked role of alliances in fostering start-up firm innovation and is consistent with Alvarez-Garrido & Dushnitsky (2016) and Chemmanur et al. (2014) who find that CVC-backed firms generate more patents than IVC-backed firms.

My second contribution is that, after implementing my matched quasi-experiment, start-ups that form an alliance with corporate investors have a 5% higher overall probability of obtaining FDA drug approval and produce over 35% more patents post investment compared to their CVC and IVC counterparts. These results are robust to corporate investor fixed effects and hold across multiple therapeutic categories. To give an estimate of the economic magnitude of this result, in the biotechnology sector alone where small U.S. firms spend over US$10 billion on R&D each year (Burrill & Company, 2013), my estimates imply that the use of alliances increase start-up firm R&D output from approximately 15% to 20%. At an aggregate level, of the annual spending on R&D in the U.S. economy, US$70 billion is by entrepreneurial firms per the National Science Foundation (2014) (c.f. US$225 billion by publicly listed firms in Compustat: Hirschey, Skiba & Wintoki, 2012). It could be, however, that corporate engagement is more valuable in the biotech

industry. However, even if engagement with corporate investors is only 10% as valuable in other industries, this implies an US$350 million annual increase in entrepreneurial firm R&D output.

In contrast, I find no significant treatment effect for CVC versus IVC. Overall success ratios are higher for CVC than IVC but selection seems to drive this difference. My combined results suggest that the mere *presence* of a corporate investor is not as important as the specific *financial contracting relationship* that is formed between the entrepreneur and corporate investor.

My third contribution explores the mechanisms through which alliances may better nurture innovation. I find that corporate financiers share up to 75% more knowledge with their portfolio firms under alliances than CVC, consistent with the notion that substantial synergies are created by pooling complimentary resources (Gomes-Casseres, Hagedoorn & Jaffe, 2006). In addition, I find that alliance investors display a greater tolerance for costly experimentation by funding an extra one to two clinical trials per drug candidate relative to VC investors. My evidence suggests that alliance contracts incentivize corporate financiers to provide greater financial and scientific support for drug experimentation which in turn drives higher innovative success rates.

The superior innovative performance of alliances does not imply that alliance and VC financing structures cannot co-exist in equilibrium. As outlined in the next two sections, there are different benefits and costs of IVC, CVC and alliance financing structures with my empirical results centered on the common support. Furthermore, the payoff for entrepreneurs (conditional on success) is significantly lower under alliance contracts than under VC agreements. This arises due to the sharing of profits between alliance partners (Beshears, 2013; Ozmel et al., 2013) and the reduced bargaining power of early-stage start-up firms vis-à-vis incumbent corporate investors (Nicholson, Danzon & McCullough, 2005). Thus, a start-up must consider the potential trade-off between a higher probability of success under an alliance contract versus the higher expected payoff (conditional on success) under a VC financing structure.

My paper contributes to three strands of the existing literature. First, my empirical findings shed light on the role of different financial contracting structures in fostering innovation. I extend the work of Chemmanur et al. (2014) and Alvarez-Garrido & Dushnitsky (2016), who find that CVC-backed firms are more innovative than IVC-backed firms, by comparing the innovative performance of strategic alliances with these two VC financing structures. Second, my research relates to the literature on organizational structure and the boundaries of the firm. Previous theoretical work that adopts the property rights approach to the theory of the firm argue that hybrid organizational forms such as alliances can optimally balance incentives of firms to contribute to a joint innovative project (Robinson, 2008; Hackbarth, Mathews & Robinson, 2014). My results support the premise that alliances can help to optimally combine inputs from multiple firms to improve R&D productivity. Third, my paper contributes to the growing body of research exploring the mechanisms that drive innovation within entrepreneurial firms (Seru, 2014; Bernstein, 2015; Ferreira, Manso & Silva, 2014; Ederer & Manso, 2013). My results suggest that the sharing of corporate financier knowledge (e.g. Chemmanur et al., 2014) and a high tolerance for experimentation (e.g. Manso, 2011; Tian & Wang, 2014) are two key channels through which financial intermediaries can foster entrepreneurial firm innovation.

The remainder of this paper is organized as follows. Section 1.2 considers the factors driving financing structure choice as predicted by property rights theory. Section 1.3 details my matched quasi-experimental research design. Section 1.4 describes the data and evidence supporting the identifying assumptions of my empirical method. Section 1.5 analyses the relationship between financing structure and portfolio firm innovation. Section 1.6 considers the mechanisms by which different financing structures promote start-up firm innovation. Section 1.7 concludes.

1.2 PROPERTY RIGHTS THEORY AND FINANCIAL STRUCTURES

In an incomplete contracting environment, a potential 'hold-up' problem can arise whereby contracting parties may refrain from making efficient (but non-contractible) relationship-specific investments (Williamson, 1975). The property rights theory of the firm approach developed in Grossman & Hart (1986) and Hart & Moore (1990) emphasizes that the allocation of the 'residual rights of control' (the power to exercise decision rights over the use of assets in cases not covered by the original contract) between the parties can be used to incentivise the holder of the relevant control right to make costly relationship-specific investments that maximise the parties' joint production (Hart, 2017). Given the highly uncertain nature of the R&D process (Hirshleifer, Hsu & Li, 2013), Aghion & Tirole (1994) show that the allocation of project control rights between entrepreneurs and their financiers can have a first order impact on firm innovative output.

Financial contracts should thus incentivise the entrepreneurial firm and its financiers to optimally aggregate their respective expertise and assets in order to promote innovation. If both the entrepreneur and financier possess distinct skills/assets that impact the likelihood of project success, Hellmann (2002) shows that optimal financing contracts must trade-off the provision of sufficient incentives for entrepreneurs and financiers. On the one hand, entrepreneurs can relinquish more control rights to financiers (Hellmann, 1998) or provide investors with greater access to the start-up firm's critical resources like its essential intellectual property and key personnel (Rajan & Zingales, 1998), thus incentivising investors to better specialize their intellectual and physical capital to the start-up firm's resources.[2] On the other hand, Lerner, Shane & Tsai (2003) and Aghion & Tirole (1994) stress the importance of adequately incentivising the entrepreneur to exploit their valuable intellectual property through relatively high ownership stakes and project management autonomy.

To optimally balance the incentives of financial contracting parties, the prior literature has identified three key factors that affect financing structure selection, namely the benefit of access to a financier's technical knowledge, the benefit of leveraging a financier's product commercialization experience and the cost of knowledge leakages to corporate financiers.

First, entrepreneurial firms should consider the extent to which a financier's technical knowledge can improve the startup firm's chance of innovative success. Corporate financiers that operate in a similar technological space as the start-up will typically possess superior industry and technological expertise relative to purely financial IVC investors (Chemmanur et al., 2014). Thus, entrepreneurs will prefer to leverage the intellectual property of corporate investors if they are not widely available or costly to replicate (Chatterji & Fabrizio, 2012; Hellmann, 2002).

Second, entrepreneurial firms may also assess the potential ability of corporate financiers to aid product commercialization and even increase the size of the start-up firm's target end market. Given the difficulty in replicating the distribution and marketing capabilities of incumbent firms in larger scale markets (Srivardhana, 2006), start-up firms may prefer to obtain financing from corporate investors in order to utilize their commercialization infrastructure and brand reputation in marketing the entrepreneur's new product or service (Chatterji & Fabrizio, 2012).[3] This preference aligns with the desire of established corporate investors to use their limited capital

[2] Survey evidence in Cumming & Johan (2013) and empirical studies by Somaya, Kim & Vonortas (2010), Dimov & Gedajlovic (2010) and Adegbesan & Higgins (2007) support these theoretical conjectures.

[3] This is likely to be more important if the start-up will face intense competition in its target market (Li et al., 2015).

and human resources to service bigger, more scalable markets (Wellman-Labadie & Zhou, 2010).

Third, a counterbalancing concern for entrepreneurs in selecting a financial contracting type is the risk associated with the potential loss of valuable trade secrets to corporate investors (or in extreme cases technology appropriation) (Matthews, 2006; Oxley, 1997; Gulati & Singh, 1998; Hitt et al., 1995). These losses are likely to be more pronounced when the start-up is pursuing a project that is quite different from prior work in that technology field (Maula et al., 2009).

In response to these property rights considerations, alternative financial contracting structures such as IVC, CVC and strategic alliances have been developed, each with differing emphasis on the role of the financier in the innovation process (Figure 1 shows the number of entrepreneurial firm financings by structure between 1985 and 2011). In particular, the payoff structure of an alliance contract is designed to elicit greater operational input by corporate financiers. Appendix 1 outlines the differences in the design of entrepreneur and corporate financier payoffs as well as the typical division of R&D responsibilities. The main differences are discussed below.

In return for the corporate financier ("alliance investor") providing R&D funding, the start-up firm will cede substantial cash flow and control rights to alliance investors. For example, as part of an early stage (pre-clinical) drug development alliance, the entrepreneurial firm will typically sign a licensing agreement granting the alliance investor rights to sell any marketable products in return for a royalty fee. Based on surveys of pharmaceutical companies conducted by Medius Associates (2001) and the Licensing Executives Society (2008), the agreed royalty rates for these early stage ventures is typically only 3-7% of future total revenues, reflecting the high risk of project failure and the relatively weaker bargaining position of young start-up firms.

Commensurate with their relatively high share of project cash flow rights, alliance investors enjoy broad project-level oversight and monitoring rights (Ozmel et al., 2013; Higgins, 2007). This is especially true in relation to product development and commercialization activities. For instance, given that corporate pharmaceutical investors possess greater accumulated knowledge of the clinical trial and regulatory review process and have pre-existing marketing infrastructure (Sytch & Bubenzer, 2008), Lerner & Merges (1998) and Higgins (2007) find that corporate investors receive the lion's share of control rights concerning the management of clinical trials, the manufacturing of drugs pre- and post-approval as well as the marketing rights for approved drugs. Corporate pharmaceutical investor involvement is particularly concentrated in the conduct of larger, more complex Phase 2 and Phase 3 trials, with alliance investors usually assuming full operational control of these pivotal trials.[4]

Thus, by protecting alliance investors against future hold-up concerns, property rights theory predicts that alliance investors should be better motivated to make valuable relationship-specific investments. Consistent with this prediction, Beshears (2013) and Gomes-Casseres et al. (2006) find that alliances induce more knowledge sharing between each partner's scientists/engineers.

In contrast, IVC and CVC investors will purchase an equity stake in the entrepreneurial firm and receive Board representation in corporate-level strategic decisions. Unlike alliances, VCs usually have negligible involvement in day-to-day management and operation of individual

[4] For 30 alliance contracts that I could obtain from the Recap database, 21 (70%) had a full handover of development responsibilities to alliance investors at the start of Phase 2 trials (with the remainder occurring during Phase 1 trials). For example, in the 2004 alliance contract between Achillion Pharmaceuticals and Gilead Sciences, it states that "based upon the clinical experience gained [by Achillion] with ACH-806 in phase 1 trials…Gilead may conduct phase 2 and phase 3 trials and will assume financial and operational responsibility for development of ACH-806."

R&D projects (Ozmel et al., 2013). Compared to alliances, the relative lack of interaction with portfolio firm operational personnel will limit information flows between CVC investors and start-ups.

Another distinguishing feature of alliance contracts is that the alliance investor will usually only receive a return on their investment if the entrepreneurial firm successfully markets its new product or service (Kim, 2011). For example, a pharmaceutical alliance investor will only begin to receive cash inflows from the venture *after* the start-up firm's new drug is approved and sold to end consumers. Thus, alliance investors may have stronger incentives to provide investee firms with sufficient financial and technical support (as well as additional time to experiment with new ideas) in order to maximize the probability that the new innovation is eventually marketed.

1.3 EMPIRICAL METHODOLOGY

The primitive specification of interest relates financing structure to start-up firm innovation:

$$Innovation_{i,s,t} = \alpha + \beta\ Financial\ Structure_{s,t} + \varepsilon_{i,s,t} \quad (1)$$

where structure choice and innovation measures are defined for firm i in structure s at time t.

However, without stronger exogeneity conditions, β in this specification gives the overall effect (selection + treatment) of financing structure on start-up innovation, not just the causal effect. For example, the characteristics of the start-up firm's chosen target market may affect both financial structure choice and the probability of future innovative success. Furthermore, higher quality entrepreneurial firms may self-select into certain financial contracting structures such as strategic alliances. While I could attempt to match firms solely on observable pre-investment firm and founder characteristics, it is unlikely that matching alone will fully account for differences in the inherent quality of the science underlying IVC-, CVC- and alliance-backed firm drugs.

1.3.1 Matched quasi-experimental research design

According to Josselin & Le Maux (2017) and Shadish, Cook & Campbell (2002), the key feature of quasi-experimental evaluation is that one needs to identify a comparison group among the non-treated observations that is as similar as possible to the treatment group in terms of pre-intervention characteristics, thus approximating the counterfactual control group in a randomized control trial. Following this definition, I define a quasi-experiment to be a research design that identifies a set of firms whose similarity of pre-treatment characteristics is such that it is "as if" IVC, CVC or alliance financing structures have been randomly assigned to these firms.

To estimate the causal effect of financing structure on entrepreneurial firm innovation, I implement a novel matched quasi-experimental research design. Initially, I level IVC-, CVC- and alliance-backed firms on intrinsic quality by exploiting the regulated phasing of clinical trials.

The advantage of my focus on the U.S. drug development industry is that there is a regulated pathway of clinical testing that all new drugs must satisfy in order to gain FDA approval. The FDA requires that firms must undertake a number of costly clinical trials to demonstrate the safety and efficacy of a new drug.[5] A key takeaway from this process is that start-up firms and

[5] A drug must typically undergo pre-clinical trials, three phases of clinical (in-human) trials (Phase 1, 2 and 3) and FDA review prior to being approved for marketing in the United States.

their investors must meet a high standard of scientific proof (less than 40% of early stage (pre-clinical) drug candidates reach Phase 2 testing per Paul et al., 2010; see also Hay et al., 2014) and incur substantial cost (out-of-pocket expenditure of c.US$50-130 million over 5+ years: Mestre-Ferrandiz et al., 2012, DiMasi et al., 2014; Paul et al., 2010) just to assess a drug candidate in Phase 2 trials. Intuitively, as drug candidates pass through randomized control trials designed to identify the highest quality prospects, the closer that the distribution of intrinsic quality within the remaining set of IVC, CVC and alliance-backed drug projects approaches random assignment.

My research design utilizes this high threshold of minimum quality to restrict my main estimation sample to IVC, CVC and alliance investments (made whilst the start-up was in pre-clinical testing) that reached at least Phase 2 clinical trials ("Phase 2+ firms"). There are several justifications for this approach. First and foremost, as discussed in Section 1.4.3, my use of clinical trial phasing minimizes the risk that selection on scientific quality explains my results. Second, given that corporate investor involvement is concentrated in the later stages of the drug development process post Phase 1 trials (see Section 1.2 discussion), the treatment effect of CVC versus alliance financing structures will be concentrated between the start of more complex Phase 2 trials and seeking regulatory approval (Czerepak & Ryser, 2008; Krieger, 2017).[6]

After identifying a set of firms with plausibly comparable intrinsic quality, I address concerns that the key observable selection factors discussed in Section 1.2 are systematically related to future innovative output by only comparing the innovative outcomes of IVC-, CVC- and alliance-backed firms with similar fundamental characteristics (X). I do this by first developing explicit measures for the expected benefit of access to a corporate investor's technical resources, the perceived risk of knowledge leakages to corporate investors and the possible benefit of leveraging a financier's commercialization experience (based on a product's end market size) that may be correlated with both financing structure choice and future firm innovative outcomes.[7]

With respect to the expected benefit of access to a corporate investor's technical resources, I use the start-up's pre-investment patent portfolio to calculate the firm's technological proximity to corporate pharmaceutical investors following Jaffe (1989) (termed *Industry technological proximity*). The intuition behind this measure is that the greater the overlap in technological activities between a start-up and potential corporate investors, the more likely it is that corporate investors will have useful technical resources (such as prior research or scientific personnel) that the start-up will seek to leverage via strategic alliance (and to a lesser extent CVC) relationships.

To measure the risk of knowledge transfers to corporate investors, I utilize a *firm patent originality* measure based on Hall et al. (2001) to identify firms with relatively more original innovations pre-investment. The rationale for this measure is that if start-ups have inventions that are quite different from other inventions in their immediate technological field then there is a greater risk that corporate investors may use CVC or alliance relationships to learn about the firm's novel technologies and trade secrets to the detriment of the start-up (Ma, 2016).

[6] Nevertheless, the tenor of my results are unchanged if I use traditional patent based outcome variables, namely the number of and citations to entrepreneurial firm patents generated in the first five years post-investment.

[7] As discussed further in Section 1.4.1.2 and Appendix 2, my vector of firm characteristics X also includes variables that may be correlated with project quality and future innovative outcomes, namely the number of patents held by the start-up firm pre-investment, *Pre number of firm patents*, and the number of patent citations to firm patents pre-investment, *Pre firm patent citations*, as well as key firm founder characteristics (the amount of research grants pre-investment, *Pre founders' NIH grants*, and the number of and citations to patents developed by the founders in prior employment, *Pre number of founder patents* and *Pre founder patent citations* respectively).

In relation to estimating the market size for a start-up's new drug product, I use the number of individuals affected by the medical condition targeted by the firm's lead drug candidate (*Disease prevalence*). Gans et al. (2002) argue that startups are more likely to partner with corporate investors when it is more costly to replicate the incumbent's supply chain and marketing assets. This is likely to be the case when the size of a drug's target population is comparatively larger.

With these pre-investment measures, I use the doubly robust inverse probability weighted regression adjustment (IPWRA) treatment effects framework of Wooldridge (2007) and Imbens (2004) to form a counterfactual control sample for each financing structure (see Appendix 2). The method through which the IPWRA approach forms these counterfactual control samples is to estimate the probability $p(s_i, x_i)$ that firm i with individual covariates x_i experiences treatment s_i (where $s_i =$ IVC, CVC or alliance) and then weight firm observations using the inverse of these estimated propensity scores (known as "inverse probability weights"). The intuition behind the use of these inverse probability weights is to assign greater estimation weight to VC-backed firms with characteristics that are more comparable to alliance-backed firms and vice versa.

To better visualize this "common support," Figure 2 shows the distribution of my empirical measures for the expected benefit of access, potential risk of knowledge leakages and estimated market size for IVC-, CVC- and alliance-backed Phase 2+ firms (Figure 3 shows the distribution of predicted probabilities of firms receiving each financing structure treatment according to their propensity score, based on the *combined* set of pre-investment characteristics). For example, for the first density plot for *Industry technological proximity*, VC-backed firms that have a low proximity score (and thus a low expected benefit of access to corporate investor technical resources), as well as alliance-backed firms with a high proximity measure/high expected benefit of access, will receive substantially reduced weight in the treatment effects estimation while overlapping firms towards the middle of the covariate distribution will receive much greater estimation weight. Thus, my empirical comparisons are focused on Phase 2+ firms with similar fundamental characteristics rather than firms with disparate pre-investment characteristics.

The key assumption underlying my matched quasi-experiment is that, *conditional* on the inverse probability weights (estimated via a propensity score function predicting financing choice using a large set of firm characteristics X) *and* a firm's drug reaching Phase 2 trials, it is "as if" financial contracting structure has been randomly assigned across firms in this common support:

$$\varepsilon_{i,s,t} \perp Financial\ Structure \mid p(X), Drug\ reaches\ Phase\ 2\ clinical\ trials \qquad (2)$$

In other words, I assume that there are no additional unobserved firm characteristics that are correlated with both financing structure choice and future innovation. Assuming that this condition holds, any significant differences in drug approvals and patenting between firms in this common support are likely to be primarily explained by the treatment effect of different financial contracting structures rather than pure selection effects. I present numerous sources of evidence in Section 1.4.3 that support my assumption that there are no systematic differences in intrinsic quality across financing structures after conditioning on advancement to Phase 2 clinical trials.

1.4 DATA

My dataset of U.S. drug development financing transactions results from combining firm, founder and investor information contained in 11 separate databases, including (a) a unique matching of both owned and licensed patents to entrepreneurial firms, (b) manually compiled data on start-up firms' individual drug developments and (c) novel hand-collected data on the identity, background and research grants/patents received by entrepreneurial firm founders.

1.4.1 Sample construction

I start with data on the 2,516 US-based biotechnology companies that received funding from venture capitalists (whether it be IVC or CVC) and/or strategic alliance partners between 1985 and 2007. This is the union of transaction data from *VentureXpert*, *Thomson Reuters Recap* and the novel pharma-specialized database *Medtrack*. To implement my matched quasi-experimental research design, my main empirical analysis is further confined to the set of startup firms that are: (a) focused on developing new drugs to treat human diseases/conditions[8] and (b) received IVC, CVC and/or alliance funding *prior* to initiating any clinical trials.[9] This requires hand matching the names of entrepreneurial firms to either the company profiles in the novel *BioCentury* or *Medtrack* databases (which provide detailed historical information on a firm's clinical trial activity) or the individual drug development profiles contained in the *ADIS International R&D Insight* database. Imposing these two requirements reduces the potential sample to 1,368 firms. Finally, in order to develop some of my patent-based measures of financing structure selection, I require that all firms must either own or license at least one granted patent that was applied for prior to the relevant investment date. This filtering process leads to a final sample of 1,314 financings of distinct U.S. drug development firms between 1985 and 2007.

Following Chemmanur et al. (2014), I classify an entrepreneurial firm as being CVC-backed if it receives pre-clinical financing from at least one CVC investor. Similarly, I categorize an entrepreneurial firm as being alliance-backed if it receives pre-clinical financing from a corporate partner via a strategic alliance. An IVC-backed firm is defined as an entrepreneurial firm that only receives funding from independent venture capitalists.

1.4.1.1 Measures of selection factors

I utilize *Industry technological proximity*, *firm patent originality* and *disease prevalence* as empirical measures of the expected benefit and cost of access to a corporate investor's technical resources. I collect information on firm patenting from two sources, the United States Patent & Trademark Office (USPTO) and the Berkeley-Fung patent database.[10] I also use the patent licensing data in the *Recap* and *Plainsite* databases to include patents that the entrepreneurial

[8] This criterion excludes biotechnology firms that are primarily focused on providing instruments and tools to assist in the drug development process (e.g. test tubes or computer programs) which do not require clinical trial data in order to obtain FDA marketing approval.

[9] Specifying that all biotechnology investments must have been made while the investee firm was in its pre-clinical phase ensures greater comparability in project risk profiles and that firms are at a similar stage of their life cycle.

[10] The Berkeley-Fung database extends the NBER Patent database until the end of 2016. Similar to the NBER database, it includes patent assignee names, the number of citations by/from a patent and a patent's application and grant year.

firm has *licensed* from third party entities for use in its own R&D activities (which are mainly comprised of patents invented by the firm's founders whilst working at a university).[11]

With respect to the expected benefit of access to a corporate investor's technical resources, I use the entrepreneurial firm's pre-investment patent portfolio to calculate the firm's technological proximity to potential corporate pharmaceutical investors[12] (*Industry technological proximity*). Following Jaffe (1989), I gauge the closeness of the pre-investment innovative activities of firm *i* and potential corporate pharmaceutical investors using patent counts in different technological classes. Technology classes are defined by the hierarchical Cooperative Patent Classification (CPC) scheme. Out of a total of approximately 650 subclasses and 7,000 "main groups" (of which approximately 200 "main groups" are most relevant to biotechnology), each patent is assigned to a primary subclass and main group. I use these "main group" classifications to identify firms in technological space.

To measure the risk of knowledge transfers to corporate investors, I utilize the *Firm patent originality* measure in Hall et al. (2001) whereby a patent is viewed as having greater originality if it cites prior patents from a wider array of technology classes. A patent's originality equals one minus the Herfindahl index of the CPC main group technology class distribution of all patents it cites. I average individual patents' originality scores to compute a firm's raw originality score. Following Bernstein (2015), *Firm patent originality* normalizes a firm's raw patent originality score by the average originality of all patents granted in the same year and technology class.

To estimate the market size for start-up's new drug, I use the number of individuals affected by the medical condition targeted by the firm's lead drug candidate (*Disease prevalence*). Annual prevalence estimates are provided by the NIH and other affiliated U.S. health agencies.

1.4.1.2 Additional observable pre-investment characteristics

While *Industry technological proximity*, *firm patent originality* and *disease prevalence* help to measure the selection of entrepreneurial firms into IVC, CVC and alliance financing structures, I compile additional patent-based measures of firm-level innovation pre-investment and hand collect information on individual firm founders to further alleviate concerns that differences in start-up firms innovative outcomes is being primarily driven by differences in intrinsic quality.

First, given that a start-up's prior innovation history may be related to its future innovative output, I calculate *Pre number of firm patents* as the total number of patents held by the start-up firm pre-investment (see Appendix 3). Since subsequent patent citations are a widely used proxy for patent quality (Hall et al., 2001; Bernstein, 2015), I also construct *Pre firm patent citations* as the number of citations made to the start-up firm's pre-investment patent portfolio in the period up to and including the first investment year, divided by the number of pre-investment patents.

Second, given the pivotal role played by individual firm founders in the strategic direction and operation of their entrepreneurial venture, I compile the patents and government research

[11] In the biotechnology industry, it is common for the founders of biotechnology firms to be employees of universities or specialist research institutes (who thus own or are assigned any patents protecting the founders' inventions). On establishing the new biotechnology firm, the firm's founders will ordinarily obtain an exclusive license to any of their relevant inventions from their university employer for use in the firm's drug development activities. The inclusion of licensed patents in innovation related analysis is important given that licensed patents comprise over 40% of the overall pre-investment patent portfolio of the entrepreneurial firms in my sample.

[12] As detailed in Appendix 3, I define a "potential" corporate pharmaceutical investor as a corporate investor that has made at least one CVC or alliance investment in the period leading up to (as well as including) the year that the firm receives its first external investment via an IVC, CVC or strategic alliance financing structure.

grants received by founders pre-investment. As a first step, I manually match entrepreneurial firm names to company profiles in the online *Relationship Science* database (which contain founder names and employment history).[13] I then hand match these founder names to inventor ID codes in the Berkeley Fung inventor patent database so as to compile the entire patenting history of the firm's founders pre-investment. *Pre number of founder patents* and *Pre founder patent citations* equal the number of and citations to patents developed by firm founders in prior employment respectively.[14] Separately, I hand match founder names to the National Institute of Health (NIH) grant database to compute *Pre founders' NIH grants* as the total amount of NIH research grants awarded to the founders of each firm over the 10 years prior to first investment (see Appendix 3).

1.4.1.3 Measures of innovation

This study employs both regulatory drug approvals and patent-based metrics to capture a drug development firm's innovativeness. I define *FDA Approval* as a dichotomous variable that equals one if the FDA approves a firm's drug for marketing in the United States. FDA approval is a particularly useful outcome measure because it is a direct product market measure of innovative success (Kerr & Nanda, 2015). Nevertheless, following the prior literature, I also employ patent-based metrics to measure firm innovation outcomes (Seru, 2014). *Post number of firm patents* equals the number of eventually granted patents that the start-up applied for in the first five years post-investment (Hall et al., 2005). Following Bernstein (2015), *Post firm patent quality* equals the number of citations that a post-investment patent receives divided by the average number of citations made to patents granted in the same year and technology class (see Appendix 3).

1.4.2 Summary statistics

Table 1 gives summary statistics for the full sample of 1,314 U.S. drug development firms. Consistent with Section 1.2, alliance-backed firms conduct research in technology fields that are closer to existing corporate investor research and target medical conditions with significantly larger disease populations. Similarly, IVC-backed firms have significantly higher patent originality vis-a-vis start-up firms funded by corporate investors, consistent with start-up firms preferring to enter into IVC relationships when there is an increased risk of valuable knowledge leakages to corporate investors (see section 1.5.2 for further discussion).

Table 2, Panel A provides summary statistics for other observable pre-investment firm and founder characteristics across the full sample of 1,314 drug development firms. Importantly, the number of patents in an entrepreneurial firm's portfolio pre-investment (*Pre number of firm patents*), the amount of competitively awarded NIH grant funding provided to firm founders pre-investment (*Pre founders' NIH grants*) and the number of patents developed by the firm's founders in prior employment (*Pre number of founder patents*) is significantly different across IVC-, CVC- and alliance-backed firms. Thus, a potential concern in relying on my entire sample of 1,314 firms is that there may be systematic differences in pre-investment firm quality across financing structures and that any such effects may not be fully accounted for by my explicit firm-

[13] If no company profile is available, I perform *Factiva* and web searches to identify the names of start-up founders.
[14] I exclude patents and citations to patents that are owned or licensed by the focal entrepreneurial firm given that they are already included in firm-level patent measures *Pre number of firm patents* and *Pre firm patent citations*.

and founder-level characteristics. I discuss in the next section how my matched quasi-experiment helps to alleviate any concerns that intrinsic project quality is the driver of my empirical results.

1.4.3 Evidence supporting identifying assumptions

The key assumption underlying my research design is that, conditional on the estimated inverse probability weights (estimated via a propensity score function predicting financing structure choice) *and* a firm's lead drug candidate reaching Phase 2 clinical trials, it is "as if" financial contracting structure has been randomly assigned across firms in the common support:

$$\varepsilon_{i,s,t} \perp Financial\ Structure \mid p(X), Drug\ reaches\ Phase\ 2\ clinical\ trials \quad (3)$$

Conditioning my analysis on investee firms reaching Phase 2 trials has the effect of levelling various measures of pre-investment firm "quality" across structures *prior to* matching.

First, both the quantity *and* quality of medical research produced by Phase 2+ IVC-, CVC- and alliance-backed firms, as measured by firm-level patent measures, is similar across structures (see Table 2, Panel C). For example, the mean number of patents held by Phase 2+ IVC-, CVC- and alliance-backed firms pre-investment is insignificantly different across structures. Also, the forward citations of Phase 2+ firm pre-investment patents, a well-accepted measure of the technological impact of a patent (Hall et al., 2001), is comparable across structures. To test if these univariate results hold in a multivariate setting, I run the following ordinary least squares (OLS) regression where the dependent variable Y_i is the natural log of one plus either *Pre number of firm patents* or *Pre firm patent citations*:

$$\begin{aligned} Y_i = \alpha + \beta_1 Alliance + \beta_2 IVC + \beta_3 Industry\ Technological\ Proximity \\ + \beta_4 Firm\ Patent\ Originality + \beta_5 Disease\ Prevalence + \phi_j + \tau_T + \varepsilon \end{aligned} \quad (4)$$

Where ϕ_j refers to therapeutic category fixed effects and τ_T refers to time fixed effects. The main objects of interest are the dummies *Alliance* and *IVC* which equal one when the start-up firm is an alliance- or IVC-backed firm respectively. The multivariate regression results in Table 2, Panel C confirm that both the quantity and quality of pre-investment patents developed by Phase 2+ IVC-, CVC- and alliance-backed firms are equivalent at the first investment year.

Second, another potential dimension of 'firm quality' relates to the scientific expertise of the firm's founders. In particular, it is possible that the overall body of past scientific work produced by the founders of CVC- and alliance-backed firms is of consistently higher quality compared to the prior scientific research of IVC firm founders. Given that NIH grants represent the largest source of external biomedical research funding in the U.S. (Morris, 2013) and are awarded via a competitive peer review process, one would assume that scientists who are consistently producing the highest quality research would receive significantly more NIH grants. However, conditional on firms reaching Phase 2 trials, Table 2 shows that there are insignificant differences in the amount of NIH funding received by firm founders across financing structures. Similarly, both the quantity and quality of founders' pre-investment patents are equivalent across structures.

A final piece of evidence supporting my assumption that Phase 2+ firms have comparable intrinsic quality comes from FDA assessments of the distinctiveness of late stage drug candidates.

Relevantly, the FDA classifies drug candidates that reach later stage clinical trials according to two criteria: (1) Chemical composition and (2) Therapeutic potential. In regards to chemical composition, a "new molecular entity" is defined as an active ingredient that has never been marketed in the United States. In relation to therapeutic potential, the FDA has a number of

mechanisms to accelerate the development and approval of drug candidates that fulfil an important unmet medical need or represent significant improvements over existing treatments. These include: (1) Granting a "fast track designation" for drugs that treat serious conditions and fill an unmet medical need[15]; (2) Allowing "accelerated approval" of breakthrough drugs based on positive intermediate clinical trial results[16] or (3) assigning a "priority review" voucher to a drug that appears to represent a significant improvement over currently available therapies.[17] Following Sorescu et al. (2003), I use these FDA determinations to define a "radical innovation" as a new drug that is both (1) a new molecular entity *and* (2) is given a fast track, accelerated approval or priority review designation.

Given that a drug's chemical distinctiveness and therapeutic benefit are primarily based on the compound's inherent characteristics and formative research, it would seem reasonable to expect that if the set of alliance-backed firms has a disproportionately high share of high quality drug candidates then this should result in alliance-backed firms having a higher percentage of "radical" new drugs. However, FDA designated characteristics of drugs reaching Phase 2 trials reveal that the percentage of radical new drug candidates produced under IVC, CVC and alliance financing structures is insignificantly different at 22%, 21% and 21% respectively (see Table 3).

An alternative concern that one may raise is that the dispersion in innovative outcomes may simply be due to VC firms pursuing more high risk innovation whilst alliance-backed firms pursue safer, more incremental innovation. However, if VC-backed firms were targeting higher risk, higher reward prospects, then we should expect that 'successful' VC-backed firms should produce more breakthrough or radical innovations relative to 'successful' alliance-backed firms. As shown in Panel A and Panel B of Table 3, however, FDA assessments of the "radicalness" of *only approved* drugs across financing structures are approximately equivalent. Furthermore, as discussed in section 1.6.2, alliance-backed firms conduct significantly more clinical trials than IVC and CVC investors with comparable drug development projects. If alliance-backed firms had a disproportionately high number of low risk "easy" drug projects, then it is hard to rationalize why alliance-backed firms would need to incur substantially more time and expense in evaluating the safety and efficacy of these drugs.

Overall, given the unlikelihood that alliance-backed firms have significantly greater intrinsic quality relative to IVC- and CVC-backed firms but that (a) their scientific discoveries are not cited to any greater extent by future inventors, (b) their founders do not receive any more NIH grants or generate any more patents than the founders of VC-backed firms producing relatively inferior scientific research *and* (c) have similar FDA designated drug radicalness characteristics, the weight of evidence suggests that my matched quasi-experiment using clinical trial phasing has successfully levelled entrepreneurial firms on intrinsic quality. This in turn permits the estimation of the causal effect of different financing structures on entrepreneurial firm innovation.

[15] A drug that receives a Fast Track designation is eligible for more frequent FDA meetings and faster response times as well as accelerated drug review assessment procedures.

[16] For certain drugs that treat serious conditions and fill an unmet medical need, the FDA will allow approval to be based on a 'surrogate' or intermediate clinical endpoint. For example, instead of waiting to learn if a cancer drug actually extends survival for cancer patients, the FDA may approve a drug based on evidence that the drug shrinks tumors (where tumor shrinkage can be determined much earlier than if patient life is actually extended).

[17] The benefit of a firm's drug receiving priority review from the FDA is that the statutory deadline for the FDA to accept or reject a firm's new drug application is reduced from 10 to 6 months.

1.5 EMPIRICAL RESULTS

Table 1 provides summary statistics for my sample of U.S. drug development firms. In relation to the post-investment innovation output of start-up firms, 11% of drugs developed by firms that are solely funded by IVC investors eventually obtain FDA approval. By comparison, CVC- and alliance-backed firms enjoy significantly higher FDA approval rates (16% and 22% respectively). The average firm in my sample produces 4.56 patents that have scaled patent citations of 0.87 in the five years post-investment. When broken down by financing structure, alliance-backed firms produce a significantly larger number of patents (7.09) relative to CVC-backed firms (4.88) who in turn produce more patents than IVC-backed firms (3.47). Similarly, alliance-backed firm patents exhibit higher quality, as measured by scaled forward citations.

1.5.1 Overall effect (no quasi-experiment)

As a starting point for examining the effect of financing structure on start-up firm innovation, I run the following regression where $Innovation\ Outcome_i$ is either: (1) *FDA approval*, a dummy variable equal to one if the entrepreneurial firm's drug ultimately obtains FDA approval; (2) *Post number of firm patents*, defined as the natural logarithm of one plus the number of post-investment firm patents and (3) *Post firm patent quality*, defined as the firm's average scaled forward citations per post-investment patent or:

$$\begin{aligned} Innovation\ Outcome_i = \alpha &+ \beta_1 Alliance + \beta_2 IVC + \beta_3 Industry\ Technological\ Proximity \\ &+ \beta_4 Firm\ Patent\ Originality + \beta_5 Disease\ Prevalence \\ &+ \beta_6 Pre\ number\ of\ firm\ patents + \beta_7 Pre\ firm\ patent\ citations \\ &+ \beta_8 Pre\ foundersNIH\ grants + \beta_9 Pre\ number\ founder\ patents \\ &+ \beta_{10} Pre\ founder\ patent\ citations + \phi_j + \tau_T + \varepsilon \end{aligned} \quad (5)$$

Where ϕ_j and τ_T refer to therapeutic category and time fixed effects respectively. The omitted financing structure category in all subsequent analysis is CVC. I use an ordinary least squares (OLS) regression model for patent-based outcome variables and a logit model for FDA approval.

Table 4 reports the OLS results for post-investment number of patents and scaled patent citations as well as logistic regression results for the probability of obtaining FDA drug approval.

The first noteworthy result is that IVC-backed firms have significantly *lower* innovation output relative to CVC-backed firms. IVC-backed firms have a 5% lower probability of obtaining FDA approval for their drugs and produce 16% less patents than their CVC firm counterparts. This is consistent with Chemmanur et al. (2014) and Alvarez-Garrido & Dushnitsky (2016) who find that CVC-backed firms exhibit superior innovation outcomes relative to IVC-backed firms.

The second key result in Table 4 is that alliance-backed firms have significantly higher innovation output relative to CVC-backed firms. In particular, drugs developed by alliance-backed firms are 6% more likely than CVC-backed drugs to gain FDA approval. In addition, the number of patents generated by alliance-backed firms is 52% higher than the quantity of patents produced by CVC-backed firms. Similarly, the quality of patents produced by alliance-backed firms post-investment is approximately 16% higher than those of CVC-backed firms.

Overall, this analysis suggests that corporate financiers are able to promote greater portfolio firm innovation than IVC investors and that, within corporate financier relationships, start-up firm innovation is better nurtured by strategic alliances than CVC financing relationships.

However, the key issue with this analysis is that the superior performance of firms supported by corporate financiers (and especially those financed by strategic alliances) is consistent with

two interpretations. On the one hand, the superior innovation outcomes of alliance-backed firms relative to VC-backed firms may be due to the superior ability of strategic alliance contracting structures to nurture innovation (treatment effect). On the other hand, it is possible that these results are explained by more promising drug candidates being systematically allocated to alliances (selection effect). Therefore, I examine whether the superior innovation performance of alliance-backed firms (relative to CVC and IVC financing structures) and CVC-backed firms (relative to IVC-backed firms) still holds after implementing my matched quasi-experiment.

1.5.2 Results from matched quasi-experimental research design

In order to disentangle the treatment and selection effect of different financing structures on entrepreneurial firm innovation, I implement the matched quasi-experimental approach described in Section 1.3. Unlike the analysis in the previous section which used the full sample of all pre-clinical biotechnology firm investments, I use the quasi-experimental research design provided by the phasing of clinical trials in order to restrict my empirical analysis to the 773 Phase 2+ firms that have plausibly equivalent intrinsic quality (see Section 1.4.3). Combined with the empirical measures described in Section 1.4.1 to account for the remaining sources of selection, I then apply the inverse probability weighted regression adjustment (IPWRA) estimator to causally estimate the effect of financing structure on start-up innovation (see Appendix 2).

The first step of the IPWRA method is to fit a multinomial logit model for the choice between IVC, CVC and alliance financing structures using the same variables as in Section 1.5.1. The results of the treatment selection model are presented in Table 5. As hypothesized in Section 1.2, start-up firms are significantly more likely to seek an alliance when they are: (a) operating in a technology field that is closer to the existing knowledge base of potential corporate investors, (b) pursuing less original innovations and (c) targeting a larger patient end market. Similarly, IVC financings are more common relative to CVC financings when a start-up firm's patent originality is relatively higher and target disease population is relatively lower.[18]

Documenting the selection of entrepreneurial firms into alternative financing structures is itself an important step in understanding the connection between financial contracting and the real economy. The results in Table 5 show that an innovative project's fundamental characteristics (i.e. potential relevance of an incumbent's technical knowledge, estimated end market size and the possibility of lost intellectual property to corporate investors) have a first order impact on the payoff and control rights structure chosen to balance the competing incentives of entrepreneurs and corporate investors. As predicted by property rights theory, the greatest payoffs and control rights are given to corporate investors via alliances when the benefits of access to an incumbent's technical and marketing resources are expected to significantly outweigh the associated costs.

Using the predicted propensity scores from the multinomial logit estimation, the IPWRA approach then estimates the potential outcome means for IVC-backed, CVC-backed and alliance-backed firms. Table 6 reports both the potential outcome means and the calculation of the average treatment effect (ATE)[19] of alternative financing structures on start-up firm innovation.

Table 6, Panel A presents ATE estimates of different financing structures on the probability of firms obtaining FDA drug approval. This is a particularly useful innovation outcome variable

[18] Note also that, once I condition my analysis on Phase 2+ firms only, pre-investment indicators of firm quality (# of patents, patent citations and founders' NIH grants) do not seem to significantly predict financing structure choice.
[19] Average treatment effects are computed as the respective difference in potential outcome means.

because it is a direct product-market measure of how well a firm can convert its innovative ideas into marketable products and increasing the pool of available drugs to counteract disease is a very important issue for policymakers (Kerr & Nanda, 2015). The estimated potential outcome means for Phase 2+ firms in column (2) indicates a 23% probability of obtaining FDA approval for the IVC financing group (conditional on commencing Phase 2 clinical trials) versus 25% for the CVC financing group and 33% for the strategic alliance financing treatment group. While the results indicate that CVC investors do not promote greater product innovation relative to IVC investors after accounting for selection, the estimated average treatment effect of implementing a strategic alliance arrangement instead of a venture capital financing structure is approximately 8% for Phase 2+ firms (significant at the 5% level). This is an economically meaningful difference in FDA approval rates because it implies that, in the biotechnology sector alone where small U.S. firms spend over US$10bn on R&D each year (Burrill & Company, 2013), the use of strategic alliances increase entrepreneurial firm R&D output from approximately 15% to 20%.

Table 6, Panel B calculates the ATE of different financing structures on the total number of patents generated post-investment by portfolio firms. The results imply that, once start-ups with similar quality and pre-investment characteristics are compared, alliance-backed firms produce 38% and 48% more patents post-investment than CVC- and IVC-backed firms respectively. In contrast, CVC-backed firms do not produce significantly more patents post-investment relative to IVC-backed peers (c.f. Chemmanur et al. 2014; Alvarez-Garrido & Dushnitsky, 2016).

Finally, Table 6, Panel C estimates the treatment effect of alternative financing structures on the average post-investment patent quality of entrepreneurial firms. The estimated potential outcome means in column (2) for scaled forward citations per post-investment patent are insignificantly different for IVC-, CVC- and alliance-backed firms. The lack of any significant ATEs in Panel C, combined with the results for the quantity of post-investment patents in Panel B, implies that corporate financiers do not appear to encourage entrepreneurial firms to produce a significantly higher quantity of patents post-investment at the expense of these individual patents being of a lower quality relative to the post-investment patents of VC-backed firms.

In summary, the evidence from my matched quasi-experimental research design indicates that a more nuanced view of the effect of different financing structures on entrepreneurial firm innovation is required. Specifically, in contrast to much of the prior literature which has emphasized that the *presence* of corporate financiers alone drives increased start-up firm innovation, I find that the *contracting structure* governing the relationship between corporate financiers and entrepreneurial firms appears to be the key driver of subsequent entrepreneurial firm innovation. In particular, once entrepreneurial firms are levelled on quality and we account for other observable firm characteristics driving selection, CVC-backed firms do not exhibit significantly better innovation outcomes compared to firms purely funded by independent venture capitalists. Rather, entrepreneurial firm innovation is only enhanced when the corporate financier also forms a deeper operational relationship with the financed firm via a strategic alliance.

1.5.3 Corporate investor fixed effects - CVC versus alliance results

Since the large corporate investors in my sample undertake a substantial number of CVC *and* strategic alliance transactions, I can also include corporate investor fixed effects in order to control for unobserved heterogeneity in the quality of individual corporate pharmaceutical investors (Lerner & Malmendier, 2010). When comparing the innovative outcomes of CVC versus strategic alliance transaction structures, my identification is driven by the variation in

portfolio firm outcomes for investments made by the *same* corporate investor. This further mitigates concerns that differences in entrepreneurial firm outcomes may simply be due to the better investment selection ability of a more informed group of strategic corporate investors.

I employ the inverse-probability weighted regression adjustment (IPWRA) methodology but now the first stage estimation is restricted to estimating the likelihood of an entrepreneurial firm choosing either a CVC or alliance financing structure. Both stages of the IPWRA approach utilize the following observable firm and founder characteristics: *Firm technological proximity*, *Firm patent originality*, *Disease prevalence*, *Pre number of firm patents*, *Pre firm patent citations*, *Pre founders' NIH grants*, *Pre number of founder patents* and *Pre founder patent citations*. I use *Firm technological proximity* (defined in Appendix 3) instead of *Industry technological proximity* in this specification because each entrepreneurial firm in this sub-sample chose to engage with a specific corporate financier through a CVC or strategic alliance relationship. Thus, I can compute the technological proximity between an entrepreneurial firm and its specific corporate investor.

Table 7 presents the results comparing the relative innovation outcomes of CVC-backed firms versus alliance funded firms controlling for corporate investor fixed effects. Similar to the results of Table 6, Phase 2+ alliance-backed firms generate 40% more patents post-investment and have a 9% higher probability of obtaining FDA approval relative to Phase 2+ CVC-backed firms. Therefore, even when the identity of the corporate investor is fixed, it appears as though the specific contracting relationship that is established between the corporate financier and the entrepreneurial firm has an important impact on entrepreneurial firm innovation.

1.5.4 Results by therapeutic categories

To further understand the main results reported in Section 1.5.2, I next examine the extent to which the out-performance of alliance-backed firms relative to VC-backed firms is concentrated in particular therapeutic categories. According to Danzon (2005), there are significant differences in the rate of regulatory approvals across alternative therapeutic or disease categories. Therefore, I split my main estimation sample of Phase 2+ firms by the four largest therapeutic categories (Cancer, Cardiovascular & Haematology, Infectious Diseases and Central Nervous System) and employ the same inverse-probability weighted regression adjustment (IPWRA) methodology as in Section 1.5.2 (using only the firm observations in the same therapeutic category).

Appendix 4 presents the results comparing the relative innovation outcomes of IVC-, CVC- and alliance-backed firms within major therapeutic categories. The first aspect to note about these results is that the relative out-performance of alliance-backed firms is prevalent across multiple therapeutic categories. Alliance-backed firms have a significantly higher probability of obtaining FDA approval for cancer, cardiovascular and infectious disease drug candidates while alliance-backed firms focused on cancer, cardiovascular and infectious disease therapeutics generate a significantly higher number of patents post-investment relative to their VC-backed peers.

Another interesting result from Appendix 4 is that the estimated treatment effects of strategic alliances are concentrated in therapeutic categories, namely cancer and cardiovascular, with the lowest overall probability of obtaining FDA approval (Hay et al., 2014). This is consistent with the theory that the pooling of complimentary knowledge and resources under strategic alliances is likely to be most beneficial when targeting the most challenging innovation problems.

1.6 POTENTIAL MECHANISMS FOR FACILITATING INNOVATION

While the evidence in the previous section suggests that the formation of an alliance between an entrepreneurial firm and a strategic corporate investor leads to improved innovative outcomes relative IVC or CVC financing relationships, it is important to identify the potential mechanisms by which strategic alliances may facilitate increased technological innovation. In this section, I examine two potential avenues through which strategic alliances may differentially affect the innovative activities of their investee firms, namely the extent of knowledge sharing between the contracting parties as well as financiers' tolerance for experimentation and failure.

1.6.1 Knowledge sharing

There is a substantial body of literature which establishes that, compared to independent firms interacting under arms-length relationships, strategic alliances promote greater knowledge flows between entrepreneurial firms and strategic corporate investors (e.g. Gomes-Casseres et al., 2006). This is often attributed to the fact that alliance contracts create formalized governance structures for joint management over project development and establish contractual mechanisms to facilitate the collaborative use of each partner's intellectual and physical assets. This in turn incentivizes the alliance partners to work cooperatively by sharing complementary knowledge and resources in furtherance of common objectives (Hellmann, 1998; Kirilenko, 2001). Indeed, the synergies created by pooling knowledge and resources are usually the justification given for entering into strategic alliance agreements (Somaya et al, 2010; Rothaermal & Deeds, 2004). Nevertheless, it remains an open empirical question as to whether strategic alliances promote greater knowledge sharing relative to other corporate financier structures like corporate venture capital and whether any increased knowledge sharing drives superior innovation outcomes.

In this section, I examine the specific question as to whether strategic alliances promote greater sharing of corporate financier knowledge with their portfolio firms. Following Gomes-Casseres et al. (2006), I develop a patent-based measure of knowledge sharing between corporate financiers and the entrepreneurial firms they fund termed *Entrepreneur-financier cross cites* (see Appendix 3). In particular, I count the number of times that an entrepreneurial firm patent applied for in the 5 years post-investment cites its corporate investor's patents. The intuition behind this measure is that an entrepreneurial firm has a "duty of candor and good faith" to disclose all prior arts (primarily previous patents) that are material to the development and patentability of its current invention (Hirshleifer et al., 2016). As such, it is assumed that if an entrepreneur cites another firm's patents more frequently then this is because the scientific research conducted by the other firm played a more important role in the development of the entrepreneurial firm's current invention (Jaffe et al., 2000; Hirshleifer et al., 2016). However, while this measure has the advantage of being based on observed post-investment behaviour for each specific financing transaction, a consequence of this knowledge sharing measure is that it cannot be calculated for IVC-backed firms where the entrepreneur has no specific corporate investor to cite. As such, my analysis on knowledge sharing is restricted to comparing CVC- and alliance-backed firms only.

Table 8, Panel A presents univariate statistics on the amount of knowledge shared by corporate financiers with their start-up portfolio firms under CVC and alliance contracting structures. Specifically, for CVC- and alliance-backed firms, I list the average citations from post-investment entrepreneur patents to their corporate financier's patents for the sample of "Phase 2+" firms (501 firms) and the sub-sample of 149 "Approved only" firms that eventually

obtained FDA approval for their new drugs. As shown in Panel A, there is significantly more knowledge sharing under strategic alliances than CVC relationships in all relevant sub-samples. For example, amongst Phase 2+ firms, the average value of *Entrepreneur-financier cross cites* for CVC-backed entrepreneurial firms is 2.12 compared with 3.45 for alliance-backed firms.

To further examine the drivers of post-investment knowledge sharing between start-up firms and their corporate financiers, I run multivariate regressions of knowledge sharing on a dummy variable *Alliance* that equals one when a strategic alliance relationship has been formed and zero if a CVC financing relationship has been formed. I include the same firm and founder pre-investment characteristics as in Section 1.4 along with corporate investor fixed effects. The results are presented in Table 8, Panel B. Across all relevant sub-samples, alliances appear to promote significantly more knowledge sharing between the entrepreneur and corporate financier. Corporate financiers share up to 75% more knowledge with their portfolio firms under strategic alliance relationships than under CVC financing structures. Therefore, in the likely event that corporate investors possess valuable scientific and clinical trial experience, it appears as though start-up firms enjoy the benefits of their corporate investor's accumulated technical knowledge and commercialization experience to a much greater extent under strategic alliance relationships.

1.6.2 Propensity for experimentation/tolerance for failure

A second mechanism that may cause strategic alliance financing structures to promote higher levels of entrepreneurial firm innovation is that corporate alliance financiers may have a greater incentive to allow experimentation with new ideas and may be more tolerant of project failure relative to VC financing structures. Given the highly risky and time-consuming nature of the innovation process (Cohen et al., 2014), studies such as Manso (2011) and Tian & Wang (2014) argue that the innovation process requires the entrepreneur to engage in a high amount of experimentation with new ideas, exposing the entrepreneur to a higher risk of failure. Therefore, it is crucial that financiers have a high degree of tolerance for experimentation (and frequent failure) in order to induce the optimal amount of innovative effort on the part of entrepreneurs.

There are a number of reasons why strategic alliances may encourage corporate financiers to be more tolerant of experimentation and failure relative to VC financing structures. First, as discussed to in Section 1.2, the alliance parties' upfront agreement on the shared objectives of the R&D collaboration, combined with the fact that a corporate investor's payoffs under an alliance are usually tied to the successful development, manufacture *and* marketing of the new product (Kim, 2011), may facilitate better alignment of incentives between entrepreneurs and financiers. As a result, corporate investors have strong incentives to provide entrepreneurial firms with sufficient financial and technical support, as well as ample time to experiment with new ideas, in order to maximize the entrepreneurial firm's probability of innovative success.

In contrast, venture capital funds face significant pressure to realize an expeditious return on their invested capital (Gompers & Lerner, 2000), potentially limiting the time and resources given to entrepreneurs to experiment with alternative approaches. Therefore, greater acceptance of a longer investment horizon may allow alliance financiers to better nurture entrepreneurial firm innovation (which by its nature is a very long and complicated process).

Second, Hellmann (1998), Kirilenko (2001) and Dessien (2005) use property rights theory to argue that providing financiers with greater input and oversight of entrepreneurial firm decision-making encourages financiers to be more risk tolerant and offer greater financial support to the entrepreneur. Given that alliances give corporate financiers much greater say over project-level

decision-making than CVC financing structures (Ozmel et al., 2013), it is possible that alliance investors will display greater tolerance for experimentation relative to CVC and IVC investors.

To empirically test this conjecture, I develop a novel measure of an investor's willingness to fund experimentation called *Propensity for experimentation*. I calculate the weighted average number of clinical trials that a start-up firm conducts in each phase of the drug development process. Given that conducting each additional clinical trial is quite a costly and time-consuming process, investors who provide financial and scientific support for additional testing are likely to be more willing to allow for experimentation with different drug dosages and disease populations.[20] The greater understanding of a drug's characteristics derived from this additional testing may in turn facilitate an increased chance of obtaining regulatory approval.

With respect to the calculation of my propensity for experimentation measure, I reflect the greater scale and costs associated with later stage clinical trials by assigning a weight of 1 for each Phase 1 clinical trials, a weight of 2 for Phase 2 clinical trials and a weight of 3 for Phase 3 clinical trials.[21] For example, if a firm reaches Phase 3 testing and conducts two Phase 1 trials, two Phase 2 trials and one Phase 3 trial, *Propensity for experimentation* equals 3 ($2 \times 1 + 2 \times 2 + 1 \times 3 = 9$, divided by the number of phases reached, in this case three).

Table 9, Panel A presents univariate statistics on the propensity for experimentation by IVC-, CVC- and alliance-backed firms for both the "Phase 2+" and "Approved Only" sub-samples. The first key observation is that strategic alliance investors have a significantly higher acceptance of entrepreneur experimentation relative to CVC and IVC investors. For example, amongst Phase 2+ firms with plausibly similar intrinsic quality, the mean value of propensity for experimentation for alliance-backed firms is 3.58 versus 2.81 and 2.71 for IVC- and CVC-backed firms respectively (difference significant at 1% level). Interestingly, even amongst successful firms that ultimately obtained FDA approval, alliance-backed firms exhibit a significantly higher propensity for experimentation relative to VC-backed firms (difference significant at 1% level). This implies that, even for eventually approved drugs, alliance investors fund significantly more clinical trials prior to filing for regulatory approval compared to CVC and IVC investors.

To examine the drivers of tolerance for experimentation post-investment, I run multivariate regressions of firm propensity for experimentation scores on dummy variables indicating whether the entrepreneurial firm had an alliance or IVC financing relationship. I include the same firm and founder pre-investment characteristics as in Section 1.4 along with therapeutic and time fixed effects. The results of this analysis are presented in Table 9, Panel B. Across all relevant sub-samples, strategic alliances appear to promote significantly more willingness for experimentation on the part of the financier and entrepreneur. This is an economically meaningful difference because it translates to alliance investors supporting an additional one to two clinical trials in order to examine a drug's safety and efficacy relative to similar IVC- and CVC-backed projects. In the next section I examine the extent to which the extra experimentation facilitated by alliance investors during drug development translates to an increased probability of innovative success.

[20] An advantage of my *Propensity for experimentation* measure over previously developed measures of "tolerance for failure" is that my measure is calculated using *current* activities undertaken by the investor in furtherance of the *current* project's success or failure. In contrast, the tolerance for failure measures in Tian & Wang (2011) and Chemmanur et al. (2014) are more backward-looking in that they use the length of time that an investor committed funding to *previous* unrelated projects that ultimately failed.

[21] I obtain qualitatively similar results if I instead use a simple average of the number of trials conducted per phase.

1.6.3 Impact of knowledge sharing/propensity for experimentation on future innovation

To further examine whether the probability of gaining FDA approval is promoted by alliance financiers sharing more knowledge with their portfolio firms and by alliance investors displaying an increased willingness to support entrepreneurial firm experimentation, I conduct two separate regressions. First, I run a logit regression of FDA Approval on the same variables described in Section 1.4 but split the alliance-backed dummy variable into two variables: *Alliance with high knowledge sharing* and *Alliance with low knowledge sharing*. An alliance is defined as having high knowledge sharing if the number of cross-citations under the alliance is above the pooled median number of cross-citations in all CVC- and alliance-backed transactions. An alliance is classified as a low knowledge sharing alliance in all remaining cases. The omitted group in this case is CVC-backed start-up firms. Second, I run a similar logit regression specification except that I split the alliance-backed dummy variable into the dummy variables *Alliance with high experimentation* and *Alliance with low experimentation*. An alliance is defined as having high/(low) experimentation if the weighted number of clinical trials conducted by the alliance partners is above/(below) the median propensity for experimentation score of all sample firms.

Table 10 reports these results. Column (1) focuses solely on the effect of knowledge sharing while column (2) focuses on the effect of propensity for experimentation only.

Regarding the impact of knowledge sharing on innovative outcomes, only the coefficient on *Alliance with high knowledge sharing* is positive and significant. This implies that the positive role of alliances in promoting start-up innovation is largely confined to situations where the corporate financier shares more proprietary knowledge with investee firms.

Similarly, with respect to the effect of propensity for experimentation on the probability of innovative success, it is primarily those alliance relationships that display a relatively high degree of willingness to engage in costly experimentation who enjoy superior FDA approval rates (see the positive and significant coefficient on *Alliance with high experimentation*).

The combined evidence in this section supports the theory that increased knowledge sharing and experimentation enhance the innovative output of entrepreneurial firms and represent two mechanisms through which strategic alliance financing structures may better nurture innovation.

1.7 CONCLUSION

In this paper, I examine how alternative financial contracting structures differ in their ability to nurture the innovative activities of their investee firms. I implement a novel matched quasi-experimental research design involving clinical trials in the U.S. drug development industry in order to minimize the possibility that my results are explained by differences in intrinsic firm quality. I find that alliance-backed firms achieve higher innovative output, as measured by FDA drug approval rates and post-investment patenting outcomes, than CVC- and IVC-backed firms while there are no significant differences between CVC- and IVC-backed firms after controlling for selection. I present evidence regarding two mechanisms that may explain the difference in innovative outcomes between strategic alliance and venture capital financing structures, namely the increased amount of knowledge sharing and product experimentation under alliances.

Overall, my results point to the crucial role of finance in promoting the knowledge economy. As we tackle more difficult problems across a range of different industries, it is increasingly difficult for one individual or one firm to provide complete solutions. As a result, property rights theory (acting through financial contracting) offers a vehicle by which to coordinate the resource sharing that will be necessary in driving technological innovation and economic growth.

1.8 TABLES

Table 1: Descriptive Statistics

This table presents summary statistics for the full sample of 1,314 drug development financing transactions. The first column provides the mean value (with standard deviations below in parentheses) for the full sample followed by the sub-sample means (with sub-sample standard deviations below in parentheses) for IVC-backed, CVC-backed and alliance-backed investee firms in columns (2), (3) and (4) respectively. The difference in means between CVC-backed and IVC-backed firms is reported in column (5) while the difference in means between alliance-backed and CVC-backed firms is given in column (6). Industry (firm) technological proximity is the cosine similarity of the entrepreneurial firm's patent portfolio and the patent portfolio of all active (firm's actually chosen) corporate pharmaceutical investors respectively. Firm patent originality is the Herfindahl index of patents cited by the firm's patents pre-investment scaled to year-technology average. Disease prevalence is the number of individuals in the U.S. affected by a drug's targeted medical condition. Post number of firm patents is the number of patents generated by the entrepreneurial firm 5 years post-investment. Post firm patent quality is defined as the number of citations received post-investment scaled to year-technology average. See Appendix 3 for further details on variable definitions. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Full Sample	IVC	CVC	Alliance	(3)-(2)	(4)-(3)
Number of observations	1,314	531	389	394		
Ex-ante entrepreneurial firm characteristics (observable at first investment year)						
Industry technological proximity	0.20	0.17	0.19	0.21	0.02*	0.02**
	(0.14)	(0.14)	(0.14)	(0.14)		
Firm technological proximity	n/a	n/a	0.16	0.20	n/a	0.04***
			(0.22)	(0.24)		
Firm patent originality	0.99	1.10	0.99	0.85	-0.11**	-0.11**
	(0.54)	(0.55)	(0.54)	(0.52)		
Disease prevalence (mil)	4.67	3.33	4.99	6.18	1.66**	1.19*
	(8.85)	(6.73)	(8.70)	(10.19)		
Ex-post entrepreneurial firm innovative outcomes						
FDA approval	0.15	0.11	0.16	0.22	0.05**	0.06**
	(0.37)	(0.36)	(0.36)	(0.37)		
Post number of firm patents	4.56	3.47	4.88	7.09	1.41***	2.21***
	(9.75)	(8.12)	(9.62)	(10.31)		
Log(1+post number of firm patents)	1.27	0.90	1.17	1.88	0.27**	0.71***
	(1.17)	(0.98)	(1.05)	(1.29)		
Post firm patent quality	0.87	0.80	0.80	1.03	0.00	0.23**
	(1.50)	(1.60)	(1.45)	(1.40)		

Table 2: Exogenous design on firm quality - Quasi-experiment using clinical trials

This table presents summary statistics for various subsets of the 1,314 drug development financing transactions (with known outcomes) between 1985 and 2007 that comprise the full sample. The first column provides the mean value (with standard deviations below in parentheses) for the overall sample followed by the sub-sample means for IVC-, CVC- and alliance-backed investee firms in columns (2), (3) and (4) respectively. Panel A contains pre-investment firm quality characteristics for the full sample of 1,314 pre-clinical investments. Panel B contains pre-investment firm quality characteristics only for the sub-sample of 773 firms that reached at least Phase 2 clinical trials. Panel C reports OLS regression estimates of the difference in pre-investment firm and founder characteristics across different financing structures for the sub-sample of 773 firms that reached Phase 2 clinical trials (robust standard errors are reported in parentheses). All variable definitions are contained in Appendix 3. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Pre-investment observable firm quality characteristics (Full sample of all preclinical investments)

	Full Sample	IVC	CVC	Alliance	(3)-(2)	(4)-(3)
Pre number of firm patents	3.66	3.06	3.71	4.24	0.65***	0.53*
	(3.51)	(2.63)	(3.82)	(4.08)		
Log(1+pre number of firm pat.)	1.34	1.25	1.36	1.47	0.11**	0.11**
	(0.59)	(0.53)	(0.60)	(0.70)		
Pre founders' NIH grants ($mm)	2.90	2.36	3.23	3.30	0.87**	0.07
	(5.45)	(4.48)	(6.04)	(5.99)		
Log(1+pre founders' NIH grants)	0.83	0.75	0.87	0.91	0.12**	0.04
	(0.93)	(0.87)	(0.97)	(0.96)		
Pre firm patent citations	3.09	2.86	3.15	3.34	0.28	0.19
	(5.79)	(5.24)	(5.65)	(6.57)		
Log(1+pre firm patent citations)	0.82	0.81	0.83	0.81	0.02	-0.02
	(0.99)	(0.96)	(1.00)	(1.03)		
Pre number of founder patents	2.90	2.12	3.11	3.75	0.99**	0.64*
	(8.18)	(6.05)	(8.63)	(9.97)		
Log(1+pre no. of founder pat.)	0.58	0.49	0.60	0.68	0.11**	0.08*
	(1.00)	(0.90)	(1.02)	(1.09)		
Pre founder patent citations	3.85	3.48	4.42	3.80	0.94*	-0.62
	(8.68)	(8.71)	(9.39)	(7.90)		
Log(1+pre founder patent cites)	0.74	0.62	0.80	0.77	0.18**	-0.03
	(1.14)	(1.09)	(1.19)	(1.13)		

Panel B: Pre-investment observable firm quality characteristics (Sub-sample reaching at least Phase II)

	Full Sample	IVC	CVC	Alliance	(3)-(2)	(4)-(3)
Pre number of firm patents	4.09	4.04	4.37	4.09	0.33	-0.28
	(3.69)	(3.02)	(4.18)	(3.83)		
Log(1+pre number of firm pat.)	1.44	1.42	1.47	1.43	0.05	-0.04
	(0.58)	(0.54)	(0.62)	(0.59)		

	Full Sample	IVC	CVC	Alliance	(3)-(2)	(4)-(3)
Pre founders' NIH grants ($mm)	3.09	3.01	3.36	3.15	0.35	-0.21
	(5.75)	(5.23)	(6.23)	(5.81)		
Log(1+pre founders' NIH grants)	0.85	0.83	0.88	0.86	0.02	-0.01
	(0.95)	(0.92)	(0.99)	(0.96)		
Pre firm patent citations	3.18	3.07	3.29	3.19	0.22	-0.10
	(5.35)	(4.12)	(5.70)	(6.11)		
Log(1+pre firm patent citations)	0.90	0.96	0.90	0.88	-0.06	-0.02
	(0.97)	(0.93)	(0.99)	(1.00)		
Pre number of founder patents	3.82	3.85	3.93	4.33	0.08	0.39
	(8.11)	(7.49)	(9.05)	(9.22)		
Log(1+pre no. of founder pat.)	0.78	0.78	0.77	0.82	-0.01	0.05
	(1.08)	(1.03)	(1.09)	(1.12)		
Pre founder patent citations	5.79	5.47	5.98	5.77	0.49	-0.21
	(8.98)	(8.49)	(8.72)	(8.62)		
Log(1+pre founder patent cites)	0.98	0.95	1.04	0.97	0.09	-0.07
	(1.22)	(1.26)	(1.28)	(1.18)		

Panel C: Multivariate regressions of pre-investment observable firm quality characteristics

Dependent variable	(1) Log(1+pre number of firm patents)	(2) Log(1+pre firm patent citations)	(3) Log(1+pre founders' NIH grants)	(4) Log(1+pre number of founder patents)	(5) Log(1+pre founder patent citations)
Alliance	-0.04	-0.05	0.02	0.12	0.00
	(0.06)	(0.09)	(0.09)	(0.11)	(0.12)
IVC	-0.05	0.08	-0.06	0.01	-0.05
	(0.05)	(0.09)	(0.08)	(0.10)	(0.11)
Industry technological proximity	0.78***	0.20	0.07*	-0.10	-0.18
	(0.16)	(0.26)	(0.27)	(0.29)	(0.33)
Firm patent originality	0.22***	0.04	-0.07	0.12	0.14
	(0.05)	(0.07)	(0.07)	(0.08)	(0.09)
Log(1+disease prevalence)	-0.01	0.06*	-0.10***	0.03	0.03
	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
Constant	1.03***	0.65***	0.92***	0.54***	0.95***
	(0.09)	(0.15)	(0.16)	(0.16)	(0.20)
Observations	773	773	773	773	773
Minimum trial phase reached	Phase 2	Phase 2	Phase 2	Phase 2	Phase 2
Therapeutic category FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.03	0.06	0.05	0.04

Note: Omitted category is CVC financing dummy.

Table 3: Exogenous design on firm quality - Additional tests

This table shows binary classifications of the chemical composition and the therapeutic potential of a new drug candidate by the FDA. *New chemical composition* equals one if the new drug is a "new molecular entity". *Potential for major therapeutic advance* equals one if the FDA deems that a drug candidate fulfils an important unmet medical need and/or represents a significant improvement over existing treatments. *Radical drug* is a dummy variable equal to one if the drug is classified as both a new chemical composition and a major therapeutic advance. Panel A shows the percentage of firm drugs in each FDA classification for the sub-sample of 773 firms reaching Phase II clinical trials and for the 210 firms obtaining FDA approval respectively. Panel B reports logit regression estimates of the likelihood of receiving a radical drug assessment by financing structure. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Panel A: FDA classifications of drug characteristics

	Full Sample	IVC	CVC	Alliance	(3)-(2)	(4)-(3)
FDA drug classification characteristics (all Phase 2+ firms)						
New chemical composition	0.61	0.61	0.61	0.60	0.00	-0.01
Potential for major therapeutic advance	0.29	0.30	0.29	0.28	-0.01	-0.01
Radical drug	0.21	0.22	0.21	0.21	-0.01	0.00
FDA drug classification characteristics (FDA approved drugs only)						
New chemical composition	0.62	0.60	0.63	0.62	0.03	-0.01
Potential for major therapeutic advance	0.41	0.43	0.39	0.41	-0.04	0.02
Radical drug	0.33	0.33	0.34	0.33	0.01	-0.01

Panel B: Multivariate regressions of likelihood of FDA radical drug designation by financing structure

Dependent variable	(1) Radical Drug	(2) Radical Drug
Alliance	0.09	-0.34
	(0.24)	(0.43)
IVC	0.08	0.06
	(0.23)	(0.46)
Industry technological proximity	0.17	-0.57
	(0.69)	(1.38)
Firm patent originality	0.02	-0.48
	(0.19)	(0.38)
Log(1+disease prevalence)	-0.69***	-0.68***
	(0.12)	(0.23)
Constant	-0.58	0.41
	(0.43)	(0.77)
Observations	773	210
Minimum trial phase reached	Phase 2	Approved only
Therapeutic category FEs	Yes	Yes
Time FEs	Yes	Yes
Adjusted/Pseudo R^2	0.09	0.17

Note: Omitted category is CVC financing dummy.

Table 4: Overall effect (*no* quasi-experiment) - results

This table reports the results of the effect of financing structures on entrepreneurial firm innovation *without* implementing my matched quasi-experimental research design using clinical trial staging. The dependent variables in columns (1), (2) and (3) are a dummy variable for whether the firm obtained FDA drug approval, the log of one plus the number of entrepreneurial firm patents (post-investment) and the average scaled quality of an entrepreneurial firm's post-investment patents respectively. All variable definitions are contained in Appendix 2. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. Robust standard errors are reported in parentheses.

Dependent variable	(1) FDA approval	(2) Log(1+post number of firm patents)	(3) Post firm patent quality
Alliance	0.36**	0.52***	0.16*
	(0.18)	(0.07)	(0.09)
IVC	-0.30*	-0.16**	0.07
	(0.18)	(0.06)	(0.10)
Industry technological proximity	0.57	-0.16	-0.21
	(0.53)	(0.19)	(0.27)
Firm patent originality	0.00	0.07	0.10
	(0.15)	(0.05)	(0.08)
Log(1+disease prevalence)	-0.01	-0.04	-0.08*
	(0.09)	(0.03)	(0.05)
Log(1+pre number of firm patents)	0.57***	0.78***	0.34***
	(0.13)	(0.05)	(0.07)
Log(1+pre firm patent citations)	0.14*	-0.02	-0.04
	(0.07)	(0.02)	(0.05)
Log(1+pre founders' NIH grants)	0.03	0.05*	0.12**
	(0.08)	(0.03)	(0.05)
Log(1+pre number of founder patents)	-0.11	0.06	0.04
	(0.11)	(0.04)	(0.08)
Log(1+pre founder patent citations)	0.25**	0.05	0.12**
	(0.09)	(0.03)	(0.06)
Constant	-0.92***	-0.13	0.13
	(0.29)	(0.12)	(0.18)
Model	Logit	OLS	OLS
Observations	1,314	1,314	1,314
Minimum trial phase reached	No restriction	No restriction	No restriction
Therapeutic category FEs	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes
Adjusted/Pseudo R^2	0.24	0.37	0.09

Note: Omitted category is CVC financing dummy.

Table 5: Determinants of financing structure selection

This table predicts the probability of entry into an IVC, CVC or strategic alliance financing structure in a multinomial logit framework for the main estimation sample of 773 firms that reached at least Phase 2 clinical trials. This estimation is used to construct the propensity score weights for the inverse-probability weighted regression adjustment (IPWRA) analysis. The explanatory variables used are industry technological proximity, firm patent originality, disease prevalence, pre number of firm patents, pre firm patent citations, pre founders' NIH grants, pre number of founder patents and pre founder patent citations. The base omitted financing structure category is set to CVC financing. All variable definitions are contained in Appendix 3. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. GMM standard errors are reported in parentheses.

Multinomial logit	IVC	Alliance
Industry technological proximity	-0.93	1.66**
	(0.73)	(0.72)
Firm patent originality	0.26*	-0.55***
	(0.15)	(0.19)
Log(1+disease prevalence)	-0.21**	0.21**
	(0.10)	(0.10)
Log(1+pre number of firm patents)	-0.19	-0.10
	(0.17)	(0.17)
Log(1+pre firm patent citations)	0.10	-0.05
	(0.09)	(0.10)
Log(1+pre founders' NIH grants)	-0.08	0.02
	(0.10)	(0.10)
Log(1+pre number of founder patents)	0.10	0.24
	(0.13)	(0.22)
Log(1+pre founder patent citations)	-0.09	-0.14
	(0.11)	(0.12)
Constant	-0.06	-0.21
	(0.43)	(0.45)
Observations	773	
Minimum trial phase reached	Phase 2	
Therapeutic category FEs	Yes	
Time FEs	Yes	
Adjusted/Pseudo R^2	0.07	

Table 6: Main results - Post-investment innovation outcomes

This table outlines the IPWRA potential outcome mean and average treatment effect (ATE) estimates for different financing structures. Columns (1) and (2) contain the IPWRA estimates for the sub-sample of 773 firms that reached at least Phase 2 trials. Panel A, Panel B and Panel C contain the potential outcome means across different financing structures (and consequent ATEs) for the probability of obtaining FDA drug approval, the number of patents generated by the entrepreneurial firm post-investment and the average scaled forward citations per post-investment patent respectively. All variable definitions are contained in Appendix 3. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. GMM standard errors are reported in parentheses.

Panel A: FDA approval

Prob(FDA approval)	(1)	(2)
Potential outcome means:		
IVC	0.24	0.23
CVC	0.25	0.25
Alliance	0.33	0.33
Average treatment effects:		
CVC – IVC	0.01	0.02
	(0.04)	(0.04)
Alliance – IVC	0.09**	0.10**
	(0.04)	(0.04)
Alliance – CVC	0.08**	0.08**
	(0.04)	(0.04)
Time fixed effects	Yes	Yes
Therapeutic fixed effects	No	Yes
Minimum trial phase reached	Phase 2	Phase 2
Observations	773	773

Panel B: Quantity of patents post-investment

Log(1+post number of firm patents)	(1)	(2)
Potential outcome means:		
IVC	1.37	1.37
CVC	1.46	1.46
Alliance	2.00	2.01
Average treatment effects:		
CVC – IVC	0.09	0.09
	(0.08)	(0.08)
Alliance – IVC	0.63***	0.64***
	(0.09)	(0.09)
Alliance – CVC	0.54***	0.55***
	(0.09)	(0.09)
Time fixed effects	Yes	Yes
Therapeutic fixed effects	No	Yes
Minimum trial phase reached	Phase 2	Phase 2
Observations	773	773

Panel C: Patent quality post-investment

Post firm patent quality	(1)	(2)
Potential outcome means:		
IVC	1.11	1.11
CVC	0.97	0.97
Alliance	1.16	1.14
Average treatment effects:		
CVC − IVC	-0.14	-0.14
	(0.14)	(0.14)
Alliance − IVC	0.05	0.03
	(0.13)	(0.13)
Alliance − CVC	0.19	0.17
	(0.14)	(0.13)
Time fixed effects	Yes	Yes
Therapeutic fixed effects	No	Yes
Minimum trial phase reached	Phase 2	Phase 2
Observations	773	773

Table 7: Corporate investor fixed effects model

This table shows the IPWRA potential outcome mean and average treatment effect (ATE) estimates for CVC versus alliance financing structures only. Columns (1) and (2) contain the IPWRA estimates for the sub-sample of 501 CVC and alliance firms that reached at least Phase 2 trials. Panel A, Panel B and Panel C contains the potential outcome means across different financing structures (and ATE) for the probability of obtaining FDA drug approval, the number of patents generated post-investment and the average scaled forward citations per post-investment patent respectively. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. GMM standard errors are reported in parentheses.

Panel A: FDA approval

Prob(FDA approval)	(1)	(2)
Potential outcome means:		
CVC	0.24	0.25
Alliance	0.34	0.34
Average treatment effect:		
Alliance − CVC	0.10**	0.09**
	(0.04)	(0.04)
Corporate investor fixed effects	Yes	Yes
Therapeutic and Time fixed effects	No	Yes
Minimum trial phase reached	Phase 2	Phase 2
Observations	501	501

Panel B: Quantity of patents post-investment

Log(1+post number of firm patents)	(1)	(2)
Potential outcome means:		
CVC	1.42	1.48
Alliance	2.17	2.07
Average treatment effect:		
Alliance − CVC	0.75***	0.59***
	(0.09)	(0.08)
Corporate investor fixed effects	Yes	Yes
Therapeutic and Time fixed effects	No	Yes
Minimum trial phase reached	Phase 2	Phase 2
Observations	501	501

Panel C: Patent quality post-investment

Post firm patent quality	(1)	(2)
Potential outcome means:		
CVC	1.00	1.00
Alliance	1.19	1.17
Average treatment effect:		
Alliance − CVC	0.19	0.17
	(0.13)	(0.14)
Corporate investor fixed effects	Yes	Yes
Therapeutic and Time fixed effects	No	Yes
Minimum trial phase reached	Phase 2	Phase 2
Observations	501	501

Table 8: Potential mechanism - Knowledge sharing

This table analyses the relationship between financing structure and knowledge sharing between financiers and entrepreneurial firms. Knowledge sharing is measured as the natural logarithm of one plus the total number of times that an entrepreneurial firm's post-investment patent cites a patent of its corporate investor. Panel A presents the mean amount of knowledge sharing for CVC and alliance financing structures across different sub-samples (standard deviations in parentheses). Panel B presents multivariate regression analysis of the key determinants of knowledge sharing post-investment between CVC and alliance-backed firms only. All variable definitions are given in Appendix 3. *, ** and *** denote statistical significance at the 10%, 5% and 1% level.

Panel A: Univariate statistics

Entrepreneur-Financier cross cites	(1) CVC	(2) Alliance	(2)-(1)
All Phase 2+ firms	2.12	3.45	1.33**
	(8.75)	(9.90)	
Approval only firm set	2.88	4.78	1.89*
	(9.92)	(8.22)	

Panel B: Multivariate regression analysis

Dependent variable	(1) Knowledge sharing	(2) Knowledge sharing	(3) Knowledge sharing	(4) Knowledge sharing
Alliance	0.23**	0.30**	0.46**	0.76**
	(0.09)	(0.14)	(0.21)	(0.38)
Firm technological proximity	0.48*	0.43	0.10	0.92
	(0.28)	(0.40)	(0.38)	(1.03)
Firm patent originality	0.08	0.01	-0.17	-0.01
	(0.10)	(0.14)	(0.29)	(0.39)
Log(1+disease prevalence)	0.00	-0.03	0.21**	-0.08
	(0.04)	(0.05)	(0.08)	(0.33)
Log(1+pre number of firm patents)	0.39***	0.48***	0.37**	0.67***
	(0.08)	(0.09)	(0.16)	(0.33)
Log(1+pre firm patent citations)	-0.03	-0.07	-0.12	-0.14
	(0.05)	(0.07)	(0.09)	(0.22)
Log(1+pre founders' NIH grants)	-0.02	0.00	-0.09	-0.24
	(0.06)	(0.07)	(0.08)	(0.16)
Log(1+pre number of founder patents)	0.01	0.14	0.35**	0.12
	(0.06)	(0.08)	(0.17)	(0.20)
Log(1+pre founder patent citations)	-0.02	-0.07	-0.31	-0.04
	(0.05)	(0.06)	(0.39)	(0.24)
Constant	-0.52***	0.41	-0.72	-1.32***
	(0.22)	(0.34)	(0.43)	(1.62)
Observations	501	501	149	149
Minimum trial phase reached	Phase 2	Phase 2	Approved only	Approved only
Corporate investor fixed effects	No	Yes	No	Yes
Therapeutic and time FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.09	0.16	0.20

Table 9: Potential mechanism - Propensity for experimentation

This table shows the relationship between financial contracting choice and the propensity for experimentation by financiers and entrepreneurial firms. Propensity for experimentation is measured as the weighted average number of clinical trials that an entrepreneurial firm conducts in each phase of the drug development process (see Appendix 3 for further details). Panel A presents the mean value of propensity for experimentation for IVC, CVC and alliance financing structures split by different sub-samples. Panel B presents multivariate regression analysis of the key determinants of the propensity for experimentation post-investment. All variable definitions are given in Appendix 3. *, ** and *** denote statistical significance at the 10%, 5% and 1% level.

Panel A: Univariate statistics

Propensity for experimentation	(1) IVC	(2) CVC	(3) Alliance	(2)-(1)	(3)-(2)
All Phase 2+ firms	2.81	2.71	3.58	-0.10	0.87***
	(1.17)	(0.93)	(1.56)		
Approval only firm set	3.24	3.17	4.15	0.07	0.98*
	(1.17)	(0.86)	(1.66)		

Panel B: Multivariate regression analysis

Dependent variable	(1) Propensity for experimentation	(2) Propensity for experimentation	(3) Propensity for experimentation	(4) Propensity for experimentation
Alliance	0.94***	0.94***	1.28***	1.25***
	(0.14)	(0.14)	(0.24)	(0.23)
IVC	0.10	0.13	0.28	0.29
	(0.24)	(0.20)	(0.24)	(0.28)
Industry technological proximity	0.19	0.11	-1.35*	-1.62**
	(0.45)	(0.44)	(0.76)	(0.75)
Firm patent originality	0.12	0.10	0.31	0.38*
	(0.12)	(0.12)	(0.21)	(0.22)
Log(1+disease prevalence)	0.08	0.05	0.02	0.01
	(0.06)	(0.06)	(0.08)	(0.09)
Log(1+pre number of firm patents)	0.21**	0.21**	0.19	0.16
	(0.10)	(0.10)	(0.16)	(0.16)
Log(1+pre firm patent citations)	0.05	0.05	-0.04	-0.03
	(0.06)	(0.06)	(0.10)	(0.10)
Log(1+pre founders' NIH grants)	0.01	0.00	-0.09	-0.06
	(0.05)	(0.06)	(0.09)	(0.09)
Log(1+pre number of founder patents)	0.09	0.10	0.35**	0.32
	(0.08)	(0.08)	(0.14)	(0.14)
Log(1+pre founder patent citations)	-0.10	-0.01	-0.28**	-0.27
	(0.06)	(0.07)	(0.11)	(0.11)
Constant	2.01***	2.09***	2.53***	2.21***
	(0.23)	(0.23)	(0.44)	(0.30)
Observations	773	773	210	210
Minimum trial phase reached	Phase 2	Phase 2	Approved only	Approved only
Therapeutic FEs	No	Yes	No	Yes
Time FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.15	0.14	0.23	0.19

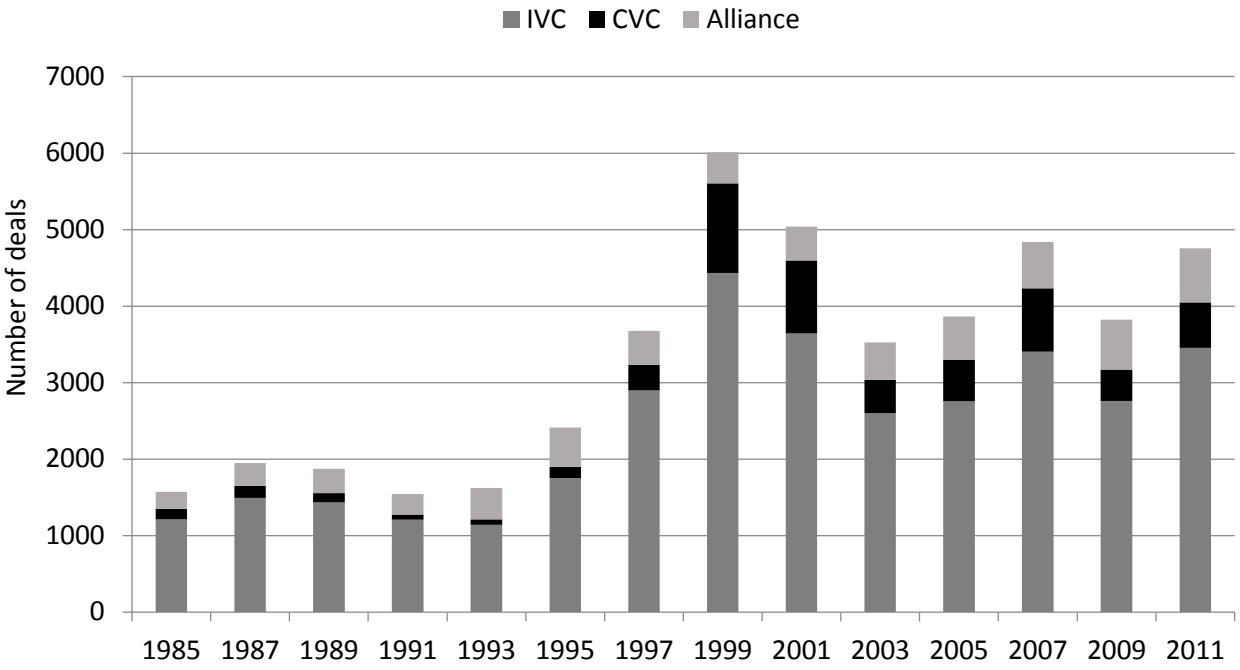
Table 10: Potential mechanisms - Effect on future innovative performance

This table reports the effect of knowledge sharing and propensity for experimentation on the probability of an entrepreneurial firm obtaining FDA approval for its new drug candidate. The dependent variable in all columns is an indicator that equals one if the biotechnology firm obtained FDA approval for its new drug and zero otherwise. Column (1) compares the innovative performance of alliance relationships with a relatively high (i.e. above median) or low amount of knowledge sharing vis-à-vis entrepreneurial firms with CVC investors. Column (2) compares the innovative outcomes of strategic alliance financings with a relatively high (i.e. above median) or low observed propensity for experimentation vis-à-vis IVC and CVC financings respectively. All variable definitions are contained in Appendix 3. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively. Robust standard errors are reported in parentheses.

Dependent variable	(1) FDA Approval	(2) FDA Approval
Alliance with high knowledge sharing	1.09***	
	(0.34)	
Alliance with low knowledge sharing	0.23	
	(0.26)	
Alliance with high experimentation		0.52**
		(0.21)
Alliance with low experimentation		0.39
		(0.28)
Industry technological proximity	0.10	0.56
	(0.54)	(0.64)
Firm patent originality	0.33	0.23
	(0.23)	(0.18)
Log(1+disease prevalence)	-0.13	-0.00
	(0.12)	(0.09)
Log(1+pre number of firm patents)	0.58***	0.47***
	(0.18)	(0.15)
Log(1+pre firm patent citations)	0.21**	0.17*
	(0.11)	(0.09)
Log(1+pre founders' NIH grants)	0.06	0.08
	(0.12)	(0.09)
Log(1+pre number of founder patents)	-0.25	-0.17
	(0.15)	(0.12)
Log(1+pre founder patent citations)	0.11	0.07
	(0.13)	(0.10)
Observations	501	773
Include IVC-backed firms?	No	Yes
Minimum trial phase reached	Phase 2	Phase 2
Corporate Investor FEs	Yes	No
Therapeutic category FEs	Yes	Yes
Time FEs	Yes	Yes
Adjusted R^2	0.13	0.07

1.9 FIGURES

Figure 1: Distribution of investments by financing structure type (all industries)



Sources: Pricewaterhouse Coopers/National Venture Capital Association Money Tree Report; Thomson Reuters; National Science Foundation; Securities Data Company (SDC).

Figure 2: Distribution of key financing selection factors by financial contracting structure

The density plots in Figure 2 show the distribution in the expected benefit of access to corporate investor technical resources (*measure: Industry technological proximity*), the potential risk of knowledge leakages to corporate investors (*measure: Firm patent originality*) and the possible benefit of a corporate investor's commercialization capabilities (*measure: Disease prevalence*) respectively for IVC-, CVC- and alliance-backed firms.

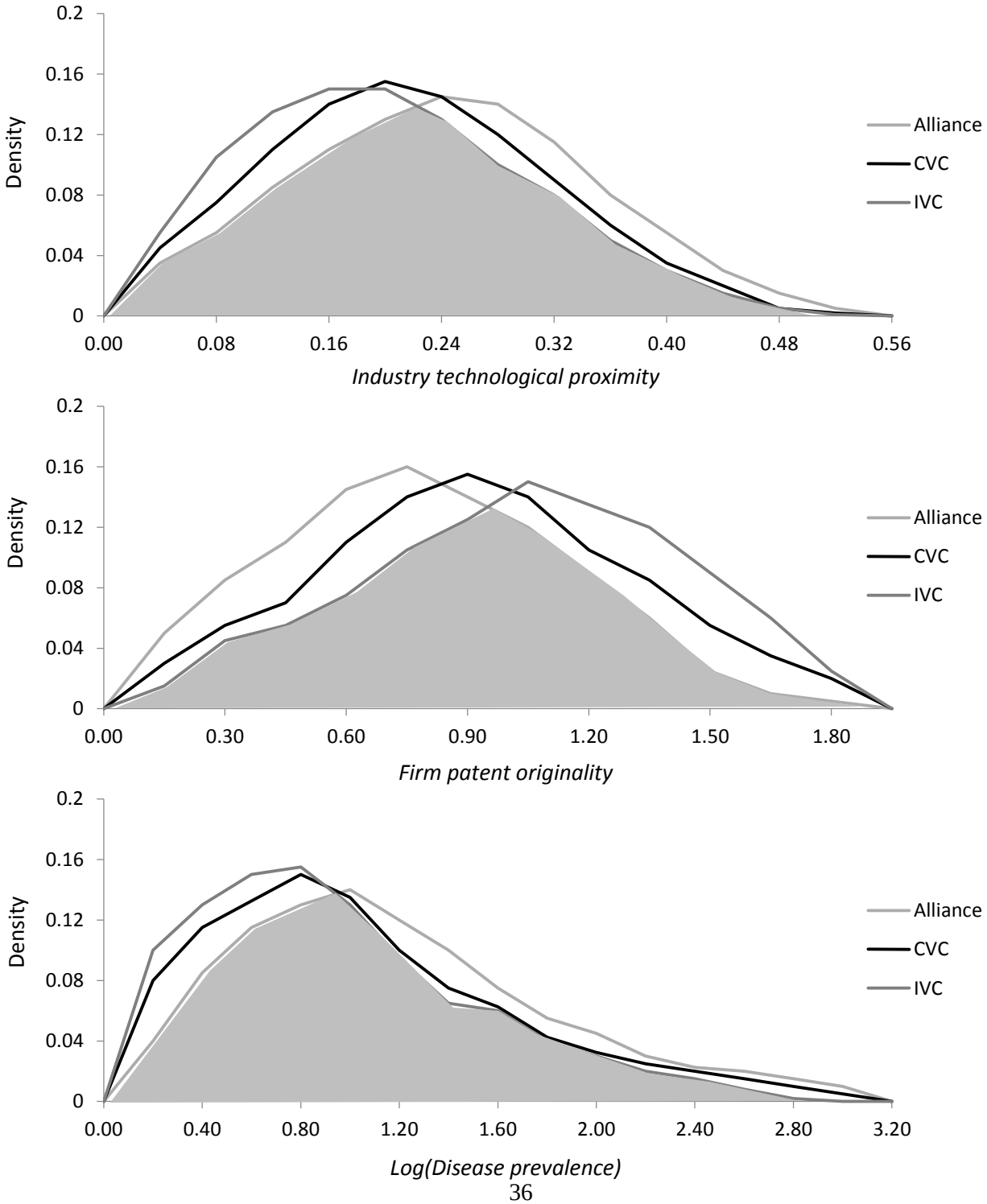
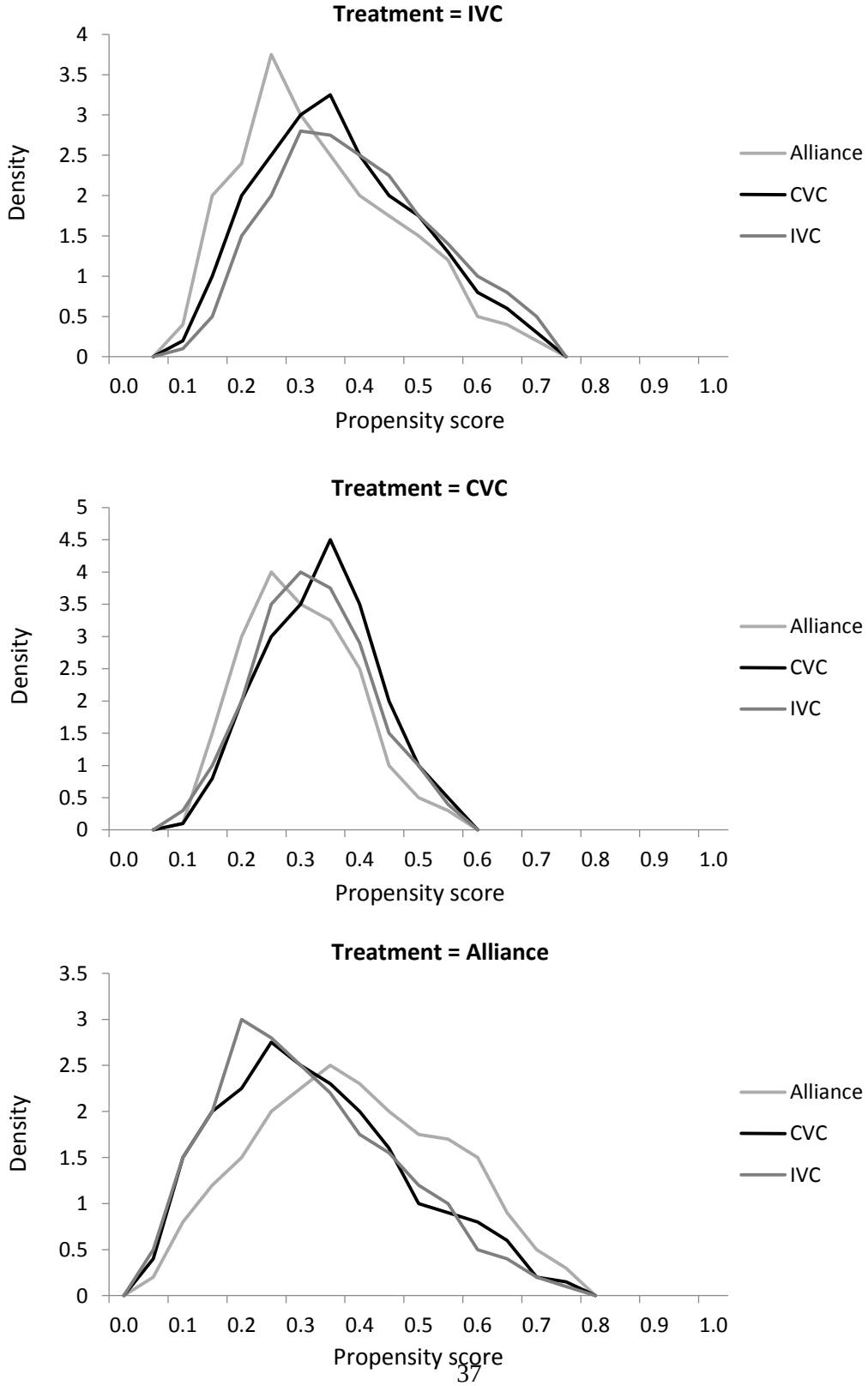


Figure 3: IPWRA - Overlap plots

The overlap plots presented in Figure 3 are the predicted probabilities of financing alternatives shown for each treatment group. For full results of the multinomial logit estimates, see Table 5.



Chapter 2:
'Til Death Do Us Part: The Relative Merits of Founder CEOs

2.1 INTRODUCTION

A fundamental question encountered by every organization is what skills and characteristics should an organization's top executive possess? In the context of for-profit corporations, the most salient manifestation of this issue is whether a firm should install a firm founder or a non-firm founder ("professional") as Chief Executive Officer (CEO). The vast economic implications of this choice between a founder and a professional CEO can be seen in the celebrated successes of founder CEO-led firms such as Amazon (Jeff Bezos), Apple (Steve Jobs), Microsoft (Bill Gates) and Facebook (Mark Zuckerberg) juxtaposed against the infamous corporate failures of other founder CEO firms such as Enron (Kenneth Lay), Worldcom (Bernard Ebbers), Jawbone (Hosain Rahman), Inphonic (David Steinberg) and Theranos (Elizabeth Holmes). This ongoing debate about the merits of founder CEOs versus professional CEOs is illustrated in the divergent views held about the advantages of a founder CEO's entrepreneurial mindset and firm-specific technical skills (Schumpter, 1934) compared with the benefits derived from the more general managerial skills of professional CEOs (Rajan, 2012; Hellmann & Puri, 2002). For example,

> "We prefer to fund companies whose founder will run the company as CEO [because] founders have the moral authority to make hard choices, they know the detail of the business and have better instincts, and they have a long-term perspective on investments and building a company that lasts."
>
> - *Ben Horowitz, Co-Founder and General Venture Capital Partner of Andreesen Horowitz*

> "[The typical founder-CEO] is the inventor, the believer, the dreamer – passionate to a fault, dismissive and intolerant of "lesser" mortals. But such people generally do not do well at more mundane tasks, like actually running a successful operation."
>
> - *Bob Lutz, Former Vice Chairman of General Motors Company*

Despite the fact that approximately 15% of all U.S. public firms are run by founder CEOs, there remains considerable disagreement in the existing literature about the role of founder CEOs in driving firm policy and ultimately firm value. On the one hand, some researchers argue that founder CEOs have a *negative* impact on firm performance (Bennett, Lawrence & Sadun, 2017; Carver, Cline & Hoag, 2013; Abebe & Alvarado, 2013; Anderson, Duru & Reeb, 2009; Johnson, Magee, Nagarajan & Newman, 1985). The claimed underperformance of founder CEOs relative to professional CEOs is attributed to founder CEOs exhibiting poorer management skills (Bennett et al., 2017) and extracting excess rents from managerial entrenchment (Brockman, Megginson, Lee & Salas, 2017; Anderson et al., 2009; Carver et al., 2013). On the other hand, many papers document a *positive* relationship between founder CEO firms and future firm performance (Kim & Koo, 2018; Lee, Kim and Bae, 2016; Olsen, Sisodiya & Swisher, 2016; Fahlenbrach, 2009; Adams, Almeida & Ferreira, 2009; Palia, Ravid & Wang, 2008; Villalonga & Amit, 2006; Nelson, 2003), asserting that this represents the treatment effect of founder CEOs in promoting technological innovation (Kim & Koo, 2018; Lee et al., 2016) and adopting a more focused M&A strategy (Fahlenbrach, 2009).

These widely divergent views about the relative merits of founder CEOs versus professional CEOs likely stem from the formidable challenge in disentangling the *treatment* effect (i.e. causal impact) of founder CEOs on future firm performance and the *selection* effects that arise from

endogenous firm-CEO matching (whereby any positive correlation between founder CEOs and future firm performance may be due to the firm founder only choosing to remain as CEO when their company is poised to innovate and succeed, even absent their involvement) (Miller, Breton-Miller, Lester & Cannella Jr., 2007; Jayaraman, Khorana, Nelling & Covin, 2000 c.f. Adams et al., 2009; Anderson & Reeb, 2003).

In this paper, I exploit a novel natural experiment involving exogenous founder CEO departures to identify the treatment effect of founder CEOs on interrelated dimensions of corporate policy and ultimately firm value. Specifically, I compare the change in the policies and performance of firms that are forced to switch from a founder CEO to a professional CEO due to the firm founder's death or serious illness (i.e. treated firms) with contemporaneous changes in the policies and performance of comparable peer firms that are able to retain their founder CEO in both the pre- and post-treatment period (i.e. control firms). Given the extensive evidence that I present supporting the identifying assumption that an individual firm founder's death or serious illness is an idiosyncratic shock that is exogenous to the firm's current and future prospects, my experimental setting is akin to some (treated) firms being randomly assigned a professional CEO while other (control) firms are randomly assigned one of the firm's founders as CEO.

There are several advantages of my empirical approach compared to traditional matching and instrumental variable estimators used in the prior literature. First, by comparing pairs of similar firms who are initially led by founder CEOs, I can credibly probe the validity of my identifying assumption by comparing the characteristics and behavior of both treated and control firms in the years *prior* to the exogenous departure of only the founder CEOs of treated firms. Unlike prior studies that try to infer causality from pre-existing founder CEO and professional CEO firms that exhibit quite divergent pre-test characteristics and behavior, I provide extensive evidence that the treated and control firms in my natural experiment are very similar on a wide range of industry-, firm- and CEO-level observables in the pre-treatment period. Second, another unique advantage of my setting is that when a founder CEO relinquishes his executive position due to death or illness, the treated firms in my sample must choose a non-firm founder/professional CEO replacement. This arises due to the simple fact that it is impossible for a firm to select another founder CEO if the company's only founder is dead or incapacitated. Thus, not only are the CEO turnovers in my study driven by credibly exogenous circumstances, the CEO characteristic that I am interested in examining (namely whether the company's CEO is a firm founder or not) cannot be directly replaced by another CEO at the treated firm Board's discretion. Third, since my sample covers a wide range of industries (39 out of 48 Fama-French industry classifications) across many different economic cycles (sample period of 40 years), I am better able to isolate the causal effect of founder CEOs on firm outcomes independent of time, macroeconomic, industry, firm and CEO-level effects (c.f. Fahlenbrach, 2009; Adams et al., 2009).

Using a difference-in-differences specification that exploits exogenous departures of founder CEOs, I initially document a number of interesting and important differences in the behavior of professional CEO-led firms vis-à-vis founder CEO-led firms. First, I find that treated firms suffer a significant decline (approximately 10%) in their internally generated innovative output after switching from a founder CEO to a professional CEO. Since the intensity of R&D investment is similar for both the treated and the control firms in pre- and post-treatment periods, this decline in internal innovation is attributable to a reduction in internal R&D productivity. Second, I find that professional CEO firms are 50% more likely than founder CEO firms to acquire companies in the years following the CEO turnover event. This increased M&A activity is primarily driven by treated firms seeking to acquire new externally developed technologies (as measured by the

number of target firm patents acquired). Third, I find that, compared to founder CEO-led firms, professional CEO-led firms take greater advantage of the tax benefits of debt finance by adopting 12% higher corporate leverage ratios. I also find that professional CEOs tend to implement less hierarchical management structures that attract and retain a deeper pool of executive talent.

The next natural question that I examine is what are the overall firm value implications of these combined changes in firm policy? I find that the value created by founder CEOs through increased internal R&D productivity is offset by the value created by professional CEOs through greater M&A activity, less conservative capital structure management and more decentralized governance structures. This results in overall firm value not being significantly different between founder CEO-led control firms and professional CEO-led treated firms in the post-treatment period. Therefore, consistent with the observed executive labor market equilibrium whereby both types of CEO co-exist, my results imply that neither type of CEO is uniformly superior and that the optimal choice between a founder CEO and a professional CEO will depend on the relative importance of internally generated innovation, external investment, capital structure and corporate governance in driving overall firm value.

I attempt to rule out several alternative explanations for my results. First, it is feasible that the observed decision-making of founder CEOs vis-à-vis professional CEOs is simply a reflection of their educational backgrounds. However, the inclusion of indicator variables for whether the firm's CEO has a PhD, MBA and/or $Technical\ Education$ (i.e. CEO has an undergraduate or graduate degree in Science, Technology, Engineering or Mathematics (STEM) related fields per Jung, 2018) does not alter my paper's findings. Second, it is possible that many of the founder CEOs in my sample are also inventors such that my results (at least with respect to innovation) are being driven by an "Inventor CEO" effect rather than a "founder effect" (Islam & Zein, 2018). However, even after including measures capturing the patenting activity of firm CEOs, I find that my results continue to hold. Finally, I include an extensive list of other firm and CEO characteristics to account for other potentially cofounding explanations, including CEO overconfidence (Hirshleifer, Low & Teoh, 2012), CEO ownership, CEO tenure and CEO early life experiences (Malmendier, Tate & Yan, 2011).

This paper contributes to several strands of the existing literature. First, my unique empirical strategy helps to shed light on the highly contested debate about the role of managerial traits in affecting corporate policy decisions (e.g. Dittmar & Duchin, 2016 c.f. Fee et al., 2013). By centering my diff-in-diff analysis on exogenous founder CEO departures while controlling for a range of both firm and CEO characteristics, I am able to more clearly identify that: (a) founder CEOs and professional CEOs adopt widely divergent strategies with respect to corporate innovation, M&A, capital structure and firm governance but that (b) both types of CEO seem to generate similar growth in overall firm value. Thus, by highlighting that both founder and professional CEOs can add value to their firms through different channels (consistent with the observed CEO market equilibrium), my study's findings help to reconcile the vast disagreement in the prior literature about the causal impact of founder CEOs on firm performance.

My research also relates to the theoretical literature on the organization of R&D (e.g. Aghion & Tirole, 1994) as well as the empirical work on the boundaries of the firm (e.g. Beshears, 2013). In particular, I find that, compared to founder CEOs, professional CEOs have a greater propensity to shift the location of some R&D activity outside firm boundaries through the acquisition of innovative target companies. This highlights how managerial characteristics and preferences can significantly impact the type of research activity conducted inside a firm's

boundaries, separate from previously documented influencing factors such as asset complementarity (Robinson, 2008) and the structure of internal capital markets (Seru, 2014).

The remainder of this paper is organized as follows. Section 2.2 presents my empirical method and data. Section 2.3 analyses the relationship between founder CEOs and firm behavior with respect to innovation, mergers and acquisitions, capital structure and corporate governance. Section 2.4 considers the impact that differences in firm behavior under founder CEOs versus professional CEOs may have on overall firm value. Section 2.5 discusses the key conclusions.

2.2 EMPIRICAL METHOD AND DATA

2.2.1 Empirical design

In order to credibly assess the relative merits of founder CEOs vis-à-vis professional CEOs, empirical tests need to isolate the causal effect of founder CEOs on various dimensions of firm policy such as innovation, M&A strategy, capital structure and corporate governance. The object of interest, the average treatment effect (ATE), can be represented as:

$$ATE = E[y_i(F = 1) - y_i(F = 0)] \tag{1}$$

where $y_i \ \ F = j$ is the observed behavior of firm i when it either has a founder CEO $\ j = 1$ or a professional CEO $\ j = 0$. The complication of making causal inferences in this setting is that we do not observe the same firm at the same point in time under two different leadership regimes. Instead, we only observe $E[y_i(1)|F = 1] - E[y_i(0)|F = 0]$ in the data, namely the difference in observed outcomes of firms led by founder CEOs relative to firms led by professional CEOs. It is important to note that:

$$\begin{aligned} E[y_i(1)|F = 1] - E[y_i(0)|F = 0] = {} & E[y_i(1)|F = 1] - E[y_i(0)|F = 1] \\ & + \underbrace{E[y_i(0)|F = 1] - E[y_i(0)|F = 0]} \end{aligned} \tag{2}$$

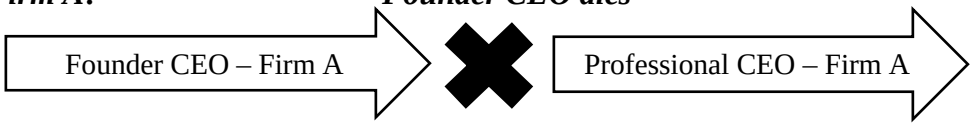
This second bracketed term is the "selection bias" that plagues any estimates based on a simple comparison in observed outcomes between founder CEO firms and professional CEO firms. This is because the difference in observed outcomes may be due to inherent differences between firms led by founder CEOs and firms led by professional CEO firms - both in terms of observable and unobservable characteristics - that are distinct from the firm's choice of CEO. This selection bias is highly unlikely to be adequately addressed using matching estimators (since companies cannot be matched on key unobservable characteristics like future innovation potential: Bernstein et al., 2016) or instrumental variable approaches (due to the difficulty in finding a robust instrument that credibly satisfies the exclusion restriction: Roberts & Whited, 2013).

However, if one could randomly assign firms with similar fundamental characteristics into either having a founder CEO or a professional CEO, one can remove this selection bias because $E[y_i(0)|F = 1] = E[y_i(0)|F = 0]$ under the condition of random assignment. Therefore, the empirical method of this paper is to exploit credibly exogenous CEO turnovers that are akin to some firms being randomly assigned a professional CEO while the remaining firms are randomly assigned one of the firm's founders as CEO.

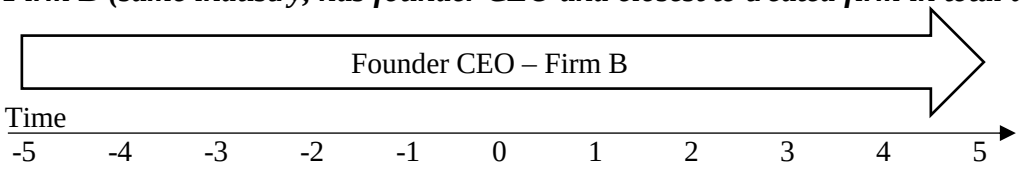
Specifically, this paper utilizes a natural experiment involving founder CEO departures due to death or illness to help generate exogenous variation in the type of CEO (i.e. founder CEO versus professional CEO) leading otherwise similar firms. In particular, I find all firms who lose their current founder CEO at time $t = 0$ as a result of the founder's death or illness (i.e. the 'treatment' group). For each treated firm, I then find another firm that: (a) is in the same industry (3-digit SIC), (b) has a founder CEO in both the pre-treatment and post-treatment periods and (c)

is closest to the treated firm in terms of total assets at year $t-1$ (i.e. the 'control' group). These two groups combined form a sample where I claim that the assignment of a firm into the treatment group (i.e. having a professional CEO in the post-treatment period due to the founder CEO's exogenous departure) or control group (i.e. the firm retains its founder CEO in the post-treatment period) is essentially random. Under this assumption of random assignment, I can then difference out any selection bias by comparing the outcomes of firms in the treatment group pre- and post-CEO turnover with those of the control group. This identification strategy can be graphically illustrated as follows:

Treated Firm A*:** ***Founder CEO dies



***Control Firm B (same industry, has founder CEO and closest to treated firm in total assets)*:**



One very attractive feature of my unique experimental research setting is that when a founder CEO relinquishes his executive position due to death or illness, the treated firms in my sample are forced to choose a non-founder/professional CEO replacement (c.f. Islam & Zein, 2018; Custodio & Metzger, 2014; Bernile, Bhagwat & Rau, 2017). While some prior papers have used 'exogenous' CEO turnovers to study the importance of other CEO characteristics such as inventor experience, financial expertise and risk-taking preferences on firm performance, the issue with this approach is that even though the turnover may occur for exogenous reasons, the choice of whether the new CEO should also possess the same given characteristic as their predecessor CEO (i.e. should the new CEO also be a financial expert, inventor etc.) is not random and likely related to the unobserved future investment/innovation prospects of the firm.

Conversely, in my typical case where a firm with only one founder loses their founder CEO due to death or illness, it is impossible for the firm to select another founder CEO to lead the company, irrespective of the firm's future outlook or optimal strategy.[22] Combined with the fact that the death or serious illness of a founder CEO occurs randomly over time, the difference in post-turnover firm behavior between treated firms (under new professional CEO leadership) and control firms (who remain under founder CEO leadership) should provide a credible estimate of the treatment effect of founder CEOs on firm outcomes.[23] In other words, identification of the

[22] Over three-fourths of my entire sample is comprised of firms whose sole founder relinquishes the CEO position due to death or illness, necessitating a mandatory switch to a non-founder/professional CEO. For all remaining cases, I do not find any treatment firms that replace a deceased co-founder with another firm co-founder as CEO.

[23] There are several reasons why it is unlikely that my results are primarily driven by the firm's *Board* making sudden and large revisions to the company's strategy after the founder CEO's death. First, there is extensive evidence that CEOs, as opposed to corporate Boards, are the primary decision-makers when it comes to operational issues such as innovation strategy, capital structure policy and management of executive officers (e.g. Graham, Harvey & Puri, 2013; Bertrand & Schoar, 2003). Second, most of the effects that I document in Section 2.3 only occur many years after the new professional CEO is appointed. This seems to be inconsistent with a story that the Board of Directors of treated firms suddenly decides that the firm's optimal strategy must change after the founder CEO departure and then merely hires a professional CEO to immediately execute this change in strategy. Finally,

causal impact of a founder CEO on firm outcomes is derived from control firms (who maintain their founder CEO throughout the test period) acting as a counterfactual for how the treated firms would have performed in the post-treatment period, had their founder CEO not passed away.

2.2.2 Sample formation

2.2.2.1 Sample of treatment firms

Following Quigley, Crossland & Campbell (2017) and Jenter, Matveyev & Roth (2016), Table 1 details the full sample of U.S. public company CEOs who were (a) one of the founders of the firm and (b) forced to permanently relinquish their CEO position due to death or illness.

First, I collect a comprehensive sample of CEO departures due to death or well-specified health issues through an extensive search of news sources, press releases, company reports, SEC company filings and various other sources. I start by searching all news articles contained in the *Factiva* database for the years 1981 to 2011 using keywords to identify the firm's CEO/top executive[24] and keywords related to death or ill-health.[25] I also search all electronically available 8-K, 10-K and proxy statement filings by firms in the *SEC EDGAR* database between 1994 and 2011. Since these keyword searches result in a large number of hits that are usually false positives, I manually screen all search results and keep only those events where I can verify that the person in question was the firm's top executive and was still in office at the date of departure. Furthermore, to ensure that no CEO departures are correlated with a firm's future prospects, I also remove any turnovers due to suicide or otherwise accompanied by any discussion that the CEO was forced to relinquish their position for any reason other than a well-defined health condition (Fee et al., 2013). This results in an initial sample of 882 CEO turnover events.

Second, consistent with the prior literature on this topic, I match all firms that experienced a CEO departure to the Compustat and CRSP databases for financial and stock price information respectively.[26] I also drop all financial firms (SIC codes 6000-6999) from my analysis. These two filters result in the loss of 305 and 40 firm observations respectively.

Third, I determine whether the departed CEO is a founder of the firm following Fahlenbach (2009). Founder status is usually given in press releases announcing the CEO's departure and/or noted in the key executive personnel section of the proxy filing. When the proxy filing does not provide information about the CEO's employment history from which I can infer whether the CEO founded the firm or not, I read both *Hoovers* and *Funding Universe* Company profiles that detail the company's history. In the rare case where these company profiles do not clearly identify the firm's founders, I use *Factiva* news searches to verify the founder status of the CEO.[27] This procedure results in a final sample of 212 exogenous founder CEO turnover events.

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the mere fact that a dying founder CEO could prevent the Board from thinking about or implementing new strategic plans is itself evidence of a significant "founder CEO effect" in corporate decision-making.

[24] Since a firm's top executive is not always referred to as the Chief Executive Officer or CEO, I follow Jenter et al. (2016) and Quigley et al. (2017) by using the following keywords to identify potential top executives: "CEO", "Chief Executive", "President", "Founder" and "Chairman".

[25] In particular, I use various connotations of keywords such as "died", "death", "passed away", "health reasons", "medical reasons", "ill health" and "illness."

[26] While restricting my sample to publicly traded firms excludes direct comparison of founder and professional CEOs in the interesting subpopulation of private firms, my focus on public firms allows for greater comparability of my results with those of the prior literature, permits consideration of a richer set of input and outcome variables and still identifies the key dimensions on which founder and professional CEOs are likely to differ across all firms.

[27] For any remaining ambiguous cases, I classify the CEO as a non-founder or professional CEO.

2.2.2.2 Sample of control firms

The control group in my natural experimental setting consists of those firms who are also run by founder CEOs in the pre-treatment period but do *not* experience the exogenous shock of losing their founder CEO. To form this control group, I start with all firms listed in Compustat in the relevant event year that are in the same 3-digit Standard Industry Classification (SIC) category as the treated firm. For each of these firms, I then identify whether the then current CEO was one of the founders of the company (i.e. a founder CEO) and continued to serve as the company's top executive for at least three years after the associated treatment firm turnover date.[28] As a final step, I use the founder CEO firm whose total book value of assets in the year prior to the turnover is closest to the total assets of the treated firm as the control firm in my difference-in-difference specifications.[29] Therefore, my control sample also comprises 212 firms.

2.2.3 Difference-in-difference estimates

I utilize a difference-in-differences specification to identify the treatment effect of founder CEOs on various firm outcomes. Since the exogenous CEO turnovers that I analyze impact only some firms and occur in different years during the sample period, I examine the before-after effect of an exogenous switch from a founder to a professional CEO (treatment group) compared to the before-after effect for firms with founder CEOs that were not affected by the turnover event (control group). This is a difference-in-differences test in multiple treatment groups and multiple time periods as considered in Atanassov (2013), Acharya, Baghai & Subramanian (2014) and Imbens & Wooldridge (2009). I implement this test via the following regression:

$$Y_{i,t} = \alpha + \beta_1 Post\ Founder\ CEO_{i,t-1} + \beta_2 Firm\ Characteristics_{i,t-1} + \beta_3 CEO\ Characteristics_{i,t-1} + Firm\ FE + Time\ FE + \varepsilon_{i,t} \quad (3)$$

where i indexes the firm and t indexes the year. The dependent variable Y denotes various innovation, M&A, governance and financial outcome variables of interest described in Section 2.2.4. The key independent variable $Post\ Founder\ CEO$ is a dummy that equals one for all years after a founder CEO relinquishes the CEO post due to death or illness, and zero otherwise. I also include an extensive set of $Firm\ Characteristics$ and $CEO\ Characteristics$ that have been identified by the prior literature as affecting a firm's subsequent output/strategy. The inclusion of firm fixed effects $(Firm\ FE)$ allows me to control for any time-invariant differences in patenting, investment and other financial practices across firms while the inclusion of year fixed effects $(Time\ FE)$ allows me to control for intertemporal technology and economic shocks. Given that the treatment is assigned at the individual firm level, I cluster standard errors by firm.

In this econometric specification, β_1 is the key coefficient of interest. By employing both firm and time fixed effects, β_1 is identified as the *within-firm* differences before and after treated firms exogenously switch from a founder CEO to a professional CEO as compared to the before and after differences for comparable control firms that did not experience the loss of their founder CEO during the same time period (Gao & Zhang, 2017; Imbens & Wooldridge, 2009).

[28] My results are qualitatively unchanged if I alternatively use a two year or a five year minimum time frame that the control firm's founder CEO must remain in office in the post-treatment period.

[29] There are 11 cases where I cannot find any founder CEO firms in the same 3-digit SIC category as the treated firm. I thus repeat the search process discussed above but consider all firms in the same 2-digit SIC category as the treated firm. My results are qualitatively unchanged if I exclude these firms from my empirical analysis.

2.2.4 Variable construction

In my empirical analysis, I first consider in Section 2.3 how founder and professional CEOs directly affect future firm behavior and/or strategy ("intermediate firm outcomes"). In particular, I examine how an exogenous change from a founder CEO to a professional CEO affects a firm's internal innovation output, M&A activity, financing decisions and corporate governance policies. I then analyze in Section 2.4 how these changes in firm behavior affect overall firm value.

2.2.4.1 Innovation variables

Given that innovation is one of the key drivers of firm growth in the modern economy (Hall & Lerner, 2010; Atanassov & Liu, 2018) and that CEOs play a critical role in spurring firm innovation (Schein, 1992; Yukl, 2002), I study the relationship between founder CEOs and internally generated corporate innovation. To gauge the success of long-term internal investment in firm innovation, I employ two measures of innovation based on patents.

My first measure of internally generated innovation is $Number\ of\ Internal\ Patents$ which represents the number of patents filed (and subsequently granted) by a firm in a given year (Gao & Zhang, 2017). I collect information on firm patenting from two sources, the United States Patent & Trademark Office (USPTO) and the Berkeley-Fung patent database.[30] As discussed further below, I identify whether a patent was internally generated by the firm or was acquired from another entity using the *Plainsite* database of patent assignment transfers.

In addition to studying the quantity of patents produced, I also measure the *quality* or impact of a patent by counting the number of citations that it receives following its approval. $Scaled\ Internal\ Citations$ equals the number of citations that a patent receives divided by the average number of citations made to patents granted in the same year and technology class. I scale the raw citation count to account for potential variation in citation rates over time and across technologies (Bernstein, 2015) as well as to address truncation bias that results in patents granted towards the end of the sample having less time to accumulate citations (Hall, Jaffe & Trajtenberg, 2005). I then form the firm-year level measure $Average\ Firm\ Patent\ Quality$ by calculating the average scaled citations across all of the firm's internally generated patents.

2.2.4.2 Acquisition related variables

Since a firm's external investment activities through modes such as M&A often has profound value consequences (both positive and negative) for firm shareholders (Moeller, Schlingemann & Stulz, 2005), I develop three measures of the intensity of a firm's acquisition activity.

First, I use the *SDC Platinum* database to identify all completed acquisitions by sample firms of private, public and subsidiary targets from 1976 to 2016. Following Gompers, Ishii & Metrick (2003), I count the number of acquisitions per firm-year $(Acquisition\ Count)$.

Second, to capture the economic importance of M&A activity to the sample firm, I compute the variable $Acquisition\ Ratio$ as the sum of the prices paid for all acquisitions made during the year, divided by the firm's market capitalization (Fahlenbrach, 2009).

Third, I use the *Plainsite* database to develop a novel measure that identifies the number of patents that a company acquires from external entities during the year ($Number\ of\ Acquired\ Patents$). Since *Plainsite* records all transfers of title to granted patents

[30] The Berkeley-Fung database extends the NBER Patent database until 2016. Similar to the NBER database, it includes patent assignee names, the number of citations by/from a patent and a patent's application and grant year.

and pending patent applications, I am able to observe patents that were originally developed by other externally owned entities and subsequently acquired by the focal firm (even if the patent is ultimately granted in the name of the acquirer). I supplement the information in the *Plainsite* database by searching the Berkeley-Fung database for all patents assigned to the target firm in both the pre- and post-merger period.

2.2.4.3 Financing decisions and corporate governance

Given that a firm's capital structure has the potential to be significantly affected by a CEO's experiences and preferences (Fee et al., 2013), I consider how a firm's leverage ratio changes after exogenous switches from a founder CEO to a professional CEO. Following Seru (2014), I measure $Leverage$ as total debt divided by total book value of assets.

Another dimension on which founder CEOs and professional CEOs may differ is the size and composition of the top management team (TMT) that they decide to establish as part of the firm's decision-making infrastructure (Peterson, Smith, Martorana & Owens, 2003). As such, I define $TMT\ Size$ as a count of the number of executive officers listed in a firm's annual proxy filings. To capture the possibility that certain types of CEOs may be more susceptible to losses of executive talent, I separately define $TMT\ Turnover$ as a count of the number of executive officers who left the firm during the course of the year.[31]

2.2.4.4 Operational performance and value creation

Given that the ultimate success or failure of a CEO's chosen policies is likely to be reflected in the operational performance of the firm (Fee et al., 2013), I consider return on assets (ROA), defined as operating income after depreciation divided by total assets, as a general measure of firm profitability (Bertrand & Schoar, 2003).

To test whether founder CEOs or professional CEOs systematically create more value for their shareholders, I examine changes in firm valuation, as measured by $Tobin's\ Q$, surrounding exogenous founder-to-professional CEO switches for the treated and control firms in my sample. I calculate $Tobin's\ Q$ as the ratio of the market value of assets to the book value of assets, where the market value of assets is defined as the book value of assets plus the market value of common stock less the book value of common stock and deferred taxes (Fahlenbrach, 2009).

2.2.4.5 Firm characteristics

I include a broad set of firm-level characteristics that have been identified by the prior literature as impacting firm behavior and strategy. These include $Firm\ Age$, $Firm\ Size$, $Cash$ holdings, ROA, spending on $R\&D$, capital expenditures $(Capex)$ and $Tobin's\ Q$ (see e.g. Seru, 2014; Gao & Zhang, 2017; Adams et al., 2009). All explanatory variables are lagged by one year. Please refer to Appendix 5 for the method used to construct these firm-level variables.

2.2.4.6 CEO characteristics

Given this paper's focus on comparing the actions of founder CEOs and professional CEOs, I include an extensive set of CEO-level characteristics that may attenuate the relationship between founder CEOs and firm behavior, namely: $CEO\ Age$, $CEO\ Duality$, $CEO\ Tenure$ (Islam &

[31] In computing $TMT\ Turnover$, I do not count any executive officer departures due to death or serious illness.

Zein, 2018) and $CEO\ Ownership$ (Kim & Lu, 2011). In addition, I also control for whether the CEO is an $Inventor\ CEO$ (Islam & Zein, 2018), is a $Female$, exhibits $Overconfidence$ (Malmendier & Tate, 2008), grew up during the $Great\ Depression$ (Malmendier, Tate & Yan, 2011), has $Military$ experience (Malmendier et al. 2011), is a $Financial\ Expert$ (Custodio & Metzger, 2014), has a PhD, has a MBA and/or has a STEM degree (i.e. $Technical\ education$) (Jung, 2018). Please refer to Appendix 5 for how these CEO-level variables are constructed.

2.2.5 Evidence supporting validity of experimental design

To make causal inferences about changes in firm outcome measures (for example innovation) for the treatment and control groups after the exogenous CEO turnover event, it is crucial that the parallel trends assumption holds in my research design. In other words, my natural experiment assumes that, in the absence of treatment (i.e. both the treatment and the control firms were able to retain their founder CEO throughout the sample period), the difference in firm outcomes between the treatment and control groups would be constant over time.

While the parallel trends assumption cannot be directly tested, one important way in which to assess the validity of the parallel trends assumption in my research setting is to examine whether the output/policies of the treatment and control firms were similar *prior* to the turnover event when both sets of firms were under founder CEO leadership (Seru, 2014).[32]

Panel A of Table 1 presents descriptive statistics on the innovativeness, acquisitiveness and financial position of firms in the treatment and control group before the exogenous CEO turnover event. Column 3 shows the statistical significance of the mean difference in various firm and CEO characteristics for the treatment and control group in the pre-treatment period. This univariate analysis indicates that the two groups are insignificantly different from one another on virtually all key pre-treatment characteristics.[33] The similarity of the treated and control firms in terms of observable characteristics pre-turnover is a first indication that the sample of founder CEO control firms are a valid counterfactual for the treated professional CEO firms. However, in order to more rigorously test the similarity of the two groups in the pre-treatment period, I now turn to a multivariate setting.

In this multivariate test, I pool all firms together and examine whether the innovative output, acquisition activity or the financial position of firms in the pre-treatment period can predict whether a firm experiences the departure of its founder CEO at time t. The logit specification of the probability that a founder departs their CEO position is:

$$Pr(Founder\ CEO\ Departs_{i,t} = 1) = \Phi(\beta_1 Innovation_{i,t-1} + \beta_2 Acquisitiveness_{i,t-1} + \beta_3 Firm\ Characteristics_{i,t-1} + \beta_4 CEO\ Characteristics + Time\ FE) \quad (4)$$

where $Innovation$ includes three-year average measures of internal innovation described in Section 2.2.4.1, $Acquisitiveness$ includes three-year average measures of firm acquisition activity described in Section 2.2.4.2, $Firm\ Characteristics$ represents firm-level financial and other information while $CEO\ Characteristics$ comprises CEO-level explanatory variables. The dependent variable $Founder\ CEO\ Departs$ takes a value of one for the treatment group in the

[32] As discussed earlier, an advantage of my experimental setting is that I do not attempt to infer causality from firms that have already endogenously chosen whether to install a founder CEO or a professional CEO. As observed in both Fahlenbrach (2009) and Adams et al. (2009) respectively, founder CEO-led firms are often smaller, have higher Tobin's Q and invest more in R&D and capital growth compared to professional CEO-led firms.

[33] Indeed, the only substantive difference between the two groups is that the founder CEOs of treated firms tend to be approximately 6 years older at the CEO turnover event date compared to the founder CEOs of control firms, an unsurprising observation given that my treated sample involves CEOs that eventually die or suffer serious illnesses.

event year and zero otherwise. The logit regression is estimated with time fixed effects and robust standard errors.

Panel B of Table 1 reports the results of this multivariate test. Consistent with the univariate results documented in Panel A, the pre-treatment characteristics of the treated and control firms are quite similar on the dimensions of innovative output, acquisition activity and financial position/performance and thus do not systematically predict which firms will be assigned to the treatment and control samples. This analysis supports my claim that the firms in my sample are as good as randomly assigned into the treatment and control groups and that the control firms who retain their founder CEO are a valid counterfactual for the treated firms who must switch to a professional CEO.

2.3 FOUNDER CEOS AND CORPORATE POLICY

As outlined in Section 2.2, I use a difference-in-differences specification to examine changes in firms' internally generated innovation, external M&A investment activity, capital structure and management team composition around exogenous founder-to-professional CEO turnovers.

2.3.1 Effect of founder CEOs on internally generated innovation

There are two competing theories concerning the relative ability of founder CEOs vis-à-vis professional CEOs to promote innovation, particularly in larger corporations. On the one hand, 'entrepreneurship theory' posits that founder CEOs are better innovators than professional CEOs because founder CEOs tend to have a longer term investment horizon (Miller, Breton-Miller & Lester, 2011) and are likely to have a greater tolerance to risk and failure (Fahlenbrach, 2009). In addition, founder CEOs with strong beliefs in entrepreneurial risk-taking may attract like-minded and talented employees who can increase a firm's innovative performance (Lee et al., 2016). On the other hand, 'corporate life cycle' theory suggests that founder CEOs may exhibit similar or even worse innovation performance than professional CEOs. This is because founder CEOs may not possess the right leadership skills to manage lower-level employees/inventors who are critical to driving the innovation process at larger, more established firms (Boeker & Wiltbank, 2005). In particular, as the scale and complexity of a firm's operations increases, the strong preference of founder CEOs to retain centralized decision making authority may stifle the development of creative solutions to the firm's widening range of problems and challenges (Campbell, Epstein & Martinez-Jerez, 2011; Wasserman, 2003).

2.3.1.1 Main results

Table 2 presents the regression results based on the diff-in-diff specification outlined in equation (3). Using $Ln(1 + Number\ of\ Internal\ Patents)$ as the dependent variable in column (1), I find that the coefficient estimate on the indicator $Post\ Founder\ CEO$ is negative (-0.10) and significant at the 5% level. This finding suggests that treated firms that are forced to switch from a founder CEO to a professional CEO suffer a large decline in the *quantity* of their internally generated innovation output relative to control firms that continue to be led by their founder CEOs. To examine whether there are also changes in the quality of patents produced, I examine the impact/quality of each internally generated patent using the scaled number of forward citations received per patent ($Average\ Firm\ Patent\ Quality$). As shown in column (2) of Table 3, I find that there is no significant difference in the average *quality* of patents

produced in the post-treatment period for founder CEO firms and professional CEO firms. Combining this result with the earlier findings documenting the decline in the quantity of internally generated patents implies that *total* internally generated innovation output declines significantly in the years after a founder CEO's exogenous departure. The economic magnitude of this overall decline in internal innovation is sizeable: changing from a founder CEO to a professional CEO leads to a decrease in the number of internally developed patents of approximately 10% (i.e. $e^{[-0.10]} - 1$).

One potential explanation for the reduction in the innovative output of treated firms (led by a professional CEO) relative to control firms (led by their founder CEO) is that professional CEOs may have deliberately curtailed R&D expenditure as part of a strategic shift away from focusing on internal innovative developments. Under this hypothesis, the R&D productivity of treated firms may be unchanged or even improve after a change to a professional CEO (see Custodio & Metzger (2014) in the context of financial expert CEOs). As such, in Column 3 of Table 2, I examine whether there are any significant differences in the intensity of R&D spending (defined as R&D expenditure divided by total assets following Fahlenbrach, 2009) by founder CEO firms vis-a-vis professional CEO firms. Interestingly, in contrast to the results in Fahlenbrach (2009), I find that, in my natural experimental setting involving exogenous CEO turnovers over a 30 year sample period, there are no significant differences in the R&D outlays of professional CEO firms and comparable founder CEO firms in the post-treatment period.[34] As such, my empirical results imply that the relative decline in the innovative output of treated firms is more likely due to an unanticipated drop in treated firms' internal R&D productivity post the founder CEO's departure rather than a deliberate curtailment of internal innovative activities by professional CEOs.

2.3.1.2 Pre-treatment trends

Before continuing, I expand on the discussion in Section 2.2.5 by providing further evidence that supports the parallel trends assumption underlying my empirical study. In particular, I define seven dummy variables ($Year-2$, $Year-1$, $Year\ 0$, $Year+1$, $Year+2$, $Year+3$ and $Year+4\ and\ afterward$), to indicate the year relative to the exogenous founder-to-professional CEO turnover event. For example, $Year\ 0$ indicates the year in which the founder CEO turnover event occurred, $Year-2$ denotes that it is two years prior to the CEO turnover event and $Year+2$ indicates that it is two years after the turnover event. I then re-estimate equation (3) by replacing the $Post\ Founder\ CEO$ indicator variable with the seven indicators described above.

Table 3 investigates the pre-and post-treatment trend in internally generated innovation between the treatment and control group. The first important result to note in Table 3 is that the coefficients on $Year-2$ and $Year-1$ are both close to zero and not statistically significant across all innovation measures and sub-samples. This suggests that there are no significant differences in innovation in the treatment and control groups *prior* to the exogenous shock of founder CEO departure due to death or illness, suggesting that the parallel trend assumption is not violated in my study.

Moreover, Table 3 suggests that most of the impact of an exogenous switch to a professional CEO occurs three or more years after the turnover event. In particular, the coefficients on $Year\ 0$

[34] As Fahlenbrach (2009) concedes in his paper, it is an open empirical question as to whether "the excess stock market performance of founder-CEO firms is a particularity of the sample period [1992–2002] of overall exceptional market performance" and "to what extent is the excess performance related to the investment behavior of founder-CEOs, and does it differ in different economic scenarios?

and $Year + 1$ are insignificant across all innovation measures while the effects of professional CEO leadership are concentrated in the three to five years after treatment. This is consistent with the view that innovation is a relatively long-term process (Hirschleifer, Hsu & Li, 2013) and thus we would not expect to see an immediate change in the innovation trajectory of the firm post-CEO turnover, especially when that turnover is not part of a planned change in firm strategy.

2.3.2 Impact of founder CEOs on external investment policy

While the results in the previous section suggest that a firm's *internal* innovative productivity declines after the exogenous departure of a founder CEO, this observation alone provides an incomplete perspective on the development of a firm's innovative growth options. This is because a company can expand its overall investment opportunity set by increasing its reliance on external technologies acquired through mergers and acquisitions (Bernstein, 2015) or strategic alliances (Seru, 2014). For example, in the context of firms that IPO versus those that withdraw their IPO filing and remain privately held entities, Bernstein (2015) finds that IPO firms offset a decline in the novelty of their internally generated innovation by substantially increasing their acquisition of externally developed patents. In fact, Hitt, Hoskisson & Ireland (1990) note that acquiring later stage innovative companies may be a cheaper (risk-adjusted) growth strategy than developing all new innovation through internal R&D investment. Therefore, it is important to consider the possibility that professional CEOs may offset a decline in internal R&D productivity with a greater reliance on acquiring innovative growth options through external investments like M&A.

2.3.2.1 Main results

As shown in the first two columns of Table 4, the treatment firms led by professional CEOs are significantly more acquisitive in the post-turnover period than comparable control firms led by founder CEOs after accounting for firm and CEO characteristics. In particular, firms headed by professional CEOs are 50% more likely than their founder CEO counterparts to engage in an M&A transaction in any given year. As an aside, it is important to note that the M&A activity findings in my study are the opposite of those in Fahlenbrach (2009) who finds that founder CEO firms make more acquisitions per year than non-founder CEO firms. These different results are possibly explained by the longer sample period used in my study as well as the fact that I do not consider the effect of any endogenous founder CEO turnovers.

Furthermore, given that corporate acquisitions can be conducted for a variety of reasons, it is not necessarily the case that this increase in M&A activity at treatment firms is motivated by the desire to purchase externally generated technologies (Bernstein, 2015). Therefore, I utilize my novel measure $Number\ of\ Acquired\ Patents$ which counts the number of patents that a firm acquires from external entities each year. Importantly, I find that while treated and control firms acquire external patents at a similar rate in the pre-treatment period, there is a 9% increase in the number of external patents in a treated firm's patent portfolio in the post-turnover period. This implies that firms led by professional CEOs make markedly greater use of M&A transactions as a means to broaden the firm's pipeline of innovative opportunities.

2.3.3 Founder CEOs and capital structure

An important but understudied facet of the behavior of founder CEOs relative to professional CEOs is their decision-making tendencies with respect to firm capital structure. Two related

strands of literature suggest that founder CEOs may be more likely to make more conservative leverage choices. First, Strebulaev & Yang (2013) argue that the puzzling observation that over 10% of public non-financial U.S. firms forego the tax benefits of debt equal to 7% of the market capitalization of their firm can be explained in part by agency costs arising through the private benefits of control (Bertrand & Schoar, 2006). Given that founder CEOs are likely to care more about the private benefits of control and their voting rights than professional CEOs (Strebulaev & Yang, 2013), it is plausible that founder CEOs may be more averse to using debt to finance their business. Second, using a survey of 800 CEOs in 22 emerging countries, Mullins & Schoar (2016) find that founder CEOs are four times more likely than professional CEOs to feel accountable to the firm's lenders and involve lenders before making any major investment decisions while professional CEOs place much greater emphasis on the importance of shareholder value maximization when setting the firm's financial policies. As a result, separate from a founder CEO's personal preferences, it is possible that founder CEOs may choose to systematically adopt lower corporate leverage ratios in order to facilitate a more harmonious relationship with the firm's debtholders (Cronqvist, Makhija & Yonker, 2012).

To test these predictions, I examine how a firm's leverage ratio changes around exogenous founder-to-professional CEO turnovers using the method described in Section 2.2. The first column of Table 5 presents the results of this analysis. I find that professional CEO-led treated firms adopt 12% higher leverage ratios relative to the average founder CEO control firm. This evidence is consistent with the survey findings in Mullins & Schoar (2016) whereby founder CEOs may be willing to adopt more conservative leverage policies relative to their professional CEO counterparts in order to balance the competing interests of debtholders and equityholders. Furthermore, my empirical evidence builds on the work by Frank & Goyal (2009) by robustly identifying a readily observable managerial trait, namely whether a firm's CEO is also one of the firm's founders, that has a large economic impact on corporate leverage decisions.

2.3.4 Founder CEOs and managerial philosophy

Despite the well accepted positive relationship between top management team (TMT) quality and firm performance (e.g. Kroll, Walters & Le, 2007; Fischer & Pollock, 2004), an open empirical question with respect to founder CEOs is how their deep psychological attachment and commitment to the success of the firm (Nelson, 2003) impacts both the size of the firm's TMT and the retention of executive talent. While a founder CEO's entrepreneurial mindset and extensive firm-specific knowledge will often be a key source of competitive advantage for the firm (Peterson et al., 2003), it is possible that a founder's great trust and confidence in their business judgment (Lee, Hwang & Chen, 2017) may lead to heightened tension between the founder CEO and his executive managers as well as reduce the number of executive officers to whom the founder CEO is willing to delegate decision-making authority. For example, Mullins & Schoar (2016) present survey evidence that finds that founder CEOs view their main task as supervising and monitoring the decisions of lower level management in contrast to professional CEOs that prioritize the selection and appraising of managers. This tendency of founder CEOs to maintain a more hierarchical management structure and to somewhat "micro-manage" the work of employees (Catella, 2018) may lead to more friction and disagreement between a founder CEO and their subordinates.[35] This in turn may result in founder CEOs choosing to maintain

[35] For example, co-founder and CEO of Tesla Motors Inc, Elon Musk, has described himself as a "nano-manager" and is widely reported as having a "domineering presence" in the company. As a result, "some high-level managers

smaller executive management teams relative to professional CEOs and may also precipitate a higher number of costly TMT departures (Zak, 2017).

In Column 2 of Table 5, I use a difference-in-differences estimation to first test whether treated firms led by professional CEOs are more likely to establish a larger team of executive officers relative to control firms that continue to be led by their founder CEO. I find that professional CEOs establish 15% larger executive management teams than their founder CEO counterparts. This equates to the top management teams (TMT) of professional CEO-led firms having an additional executive officer compared to founder CEOs' average TMT size of five executives. This general result is consistent with the survey evidence in Mullins & Schoar (2016) who find that founder CEOs tend to centralize control of their firm and have the fewest number of managers reporting directly to them.

While professional CEOs prefer to *add* a wider range of executive talent compared to founder CEOs, it is unclear whether the differing management styles of founder CEOs and professional CEOs systematically leads to more *losses* of executive talent. Thus, in Column 3 of Table 5, I test whether founder CEO-led firms experience a higher number of executive officer departures relative to professional CEO-led firms in the post-treatment period. I find that founder CEO firms are almost twice as likely to experience an executive departure in a given year compared to similar professional CEO firms. This finding is consistent with the theory that the authoritative management style of founder CEOs can cause greater TMT instability and turnover. This in turn may negatively impact the performance of founder CEO firms relative to professional CEO firms who are better able to acquire and keep executive human capital (see Le, Kroll & Walters, 2017).

2.4 CEO CHOICE AND FIRM VALUE

As documented in the previous section, the contrasting growth and managerial strategies of founder CEOs versus professional CEOs may (or may not) generate value for their respective shareholders. In particular, founder CEOs seem to foster superior internal R&D productivity at their firms relative to their professional CEO counterparts while professional CEOs exhibit an increased willingness to acquire externally developed technologies, take greater advantage of the tax benefits of debt financing (through increased corporate leverage) and demonstrate a greater ability to both attract and retain managerial talent. Given the stark differences in the skills and behavior of founder CEOs relative to professional CEOs, combined with the unclear value implications of each difference in firm policy considered in Section 2.3, a natural question for company stakeholders to ask is whether either type of CEO has a greater positive impact on *overall* firm value and operating performance.

2.4.1 Firm operational performance

Following the prior literature, I use an accounting measure of profitability, namely return on assets (ROA), to evaluate any changes in a firm's operating performance around the exogenous founder CEO turnover event (Bertrand & Schoar, 2003; Seru, 2014). I implement the difference-in-differences specification described in equation (3) and report the results in the first column of Table 6. Interestingly, I find that there is *no* significant difference in the operating performance

quit or were fired after clashing with the Chief Executive over Mr Musk's insistence on doing things his way, according to interviews with dozens of current and former Tesla executives" per the Wall Street Journal, "Electric Car Pioneer Elon Musk Charges Head-On at Detroit" (11 January 2015).

of treated and control firms in the post-treatment period. This implies that the beneficial impact of higher internal R&D productivity at founder CEO control firms can be offset by the superior ability of professional CEOs to: (a) acquire and integrate new external technologies into the firm's operations and (b) fully utilize the knowledge and experience of their larger, more stable executive management teams. Nevertheless, given the potential issues in using ROA as a proxy for true economic profitability (see Fee et al., 2013), I also consider how an alternative market based measure of firm value changes around the exogenous CEO turnover events in my sample.

2.4.2 Firm valuation

To make stronger causal claims about the relationship between founder CEOs and overall firm value, I use my difference-in-differences specification detailed in Section 2.2 to examine how firm value evolves for treated and control companies around exogenous shocks generated by the departure of founder CEOs for health-related reasons. Following papers such as Fahlenbrach (2009) and Adams et al. (2009), I use $Tobin's\ Q$, defined as the ratio of the market value of assets to the book value of assets, as my measure of firm value (see Appendix 5 for further details). Notably, consistent with the ROA results reported in the previous section, I find that there are *no* significant differences in overall firm value generated by treated and control firms in the post-treatment period despite these firms being run by professional CEOs and founder CEOs respectively (see last column of Table 6).

The neutral total value impact of an exogenous switch from a founder CEO to a professional CEO has numerous implications for practitioners and academics. Given that novel innovations have been shown to generate significant value (see Hall, Jaffe & Trajtenberg, 2005; Kogan, Papanikolaou, Seru & Stoffman, 2017), observing no change in overall firm value implies that firms in the treatment group were able to implement strategies that mitigated the value loss resulting from a decline in treated firms' internal R&D productivity. Thus, while it seems that professional CEOs are unable to replicate the "creative genius" of the firm's founder in terms of nurturing internally driven innovative activities, my research shows that it is insufficient to only consider internal innovation performance when evaluating the relative merits of founder CEOs and professional CEOs (c.f. Kim et al., 2018).

In particular, my findings indicate that professional CEO-led firms are better able to generate firm value through a combination of: (a) moving R&D activity outside the boundaries of the firm via the acquisition of external technologies, (b) increasing corporate leverage to take advantage of the tax benefits of debt finance and/or (c) implementing management structures that attract and retain a deeper pool of executive talent. While it is not feasible in my empirical setting to separately identify the individual value generated by each of these three strategic actions, my empirical results support the notion that a company CEO possessing a broad range of skills across M&A, firm financing and employee management activities is valuable in and of itself and is at least as important for firm growth as the promotion of internally generated innovation.

2.5 CONCLUSION

A firm's choice of CEO is one of the most important determinants of a firm's future growth and development. In this paper, I examine a question that faces every firm at least once in its lifetime, namely whether one of the firm's founders should act as the company's top executive. In order to overcome the formidable identification challenges that arise from the endogenous matching of founder CEOs and professional CEOs with the firms they manage, I exploit a

natural experiment involving exogenous founder-to-professional CEO turnovers that arise from a firm founder's death or illness. By isolating pairs of comparable founder CEO-led firms that only differ in whether they are exposed to the exogenous shock of losing their founder CEO due to health-related issues, I am able to present credibly causal estimates of the relative impact of founder CEOs on corporate policy and firm performance vis-à-vis professional CEOs.

Using my experimental setting, I first document that treated firms led by professional CEOs exhibit significantly different behavior compared to control firms that continue to be led by their founder CEOs. First, I find that professional CEO firms have 10% lower internally generated innovative output compared to founder CEO firms. Given that the amount spent on R&D is similar for both sets of firms, this decline in internal innovative output at treated firms is primarily driven by a reduction in R&D productivity. Second, I find that professional CEO firms are 50% more likely than their founder CEO counterparts to engage in M&A transactions and that one of the primary motivations for this increased M&A activity is to gain access to externally generated technologies. Third, I find that, compared to founder CEO-led firms, professional CEO-led firms adopt 12% higher corporate leverage ratios and also implement management structures that attract and retain a deeper pool of executive talent.

Given the conflicting firm value implications of these changes in corporate policy, I then examine whether these combined changes in firm policy or behavior by professional CEO firms has a clear positive or negative impact on overall firm value. I find that the observed changes in innovation, M&A, capital structure and governance policies appear to have offsetting effects such that overall firm value is not significantly different between founder CEO firms and professional CEO firms in the post-treatment period.

Overall, my results imply that founder CEOs are not uniformly superior to professional CEOs and vice-versa. Instead, it seems that each CEO type possesses particular skills that are important for driving firm value, namely founder CEOs are better able to nurture internally generated innovation while professional CEOs are more adept at managing M&A, capital structure and governance activities. These findings are consistent with the observed executive labor market equilibrium where we see that: (a) there exist a significant percentage of both founder CEO-led firms and professional CEO-led firms in the economy (Fahlenbrach, 2009; Adams et al., 2009) and (b) a firm's founder is relatively more likely to be the CEO of the firm in its early growth stages (when promoting internal innovation is likely to be relatively more important) and that professional CEOs are relatively more common among mature publicly traded firms (when capital structure, team management skills and growth through external investments is likely to be relatively more important drivers of firm value) (Hellmann & Puri, 2002; Mullins & Schoar, 2016). As a result, my study's findings support a "horses for courses" approach to firm CEO selection whereby the optimal choice between a founder CEO and a professional CEO will largely depend on the relative importance of internal innovation, external investment, capital structure and management style in driving changes in overall firm value.

2.6 TABLES

Table 1: Summary statistics and evidence supporting validity of experimental design

This table reports tests of the validity of the control group in my natural experiment. In Panel A, I provide summary statistics (mean value; standard deviations below in parentheses) as well as univariate comparisons of various firm and CEO characteristics for firms in the treatment sample (i.e. firms forced to switch from a founder CEO to a professional CEO due to death or illness of the firm founder) and firms in my control sample (i.e. firms that remain under founder CEO leadership in the pre- and post-treatment periods). Panel B presents the results of a logit regression concerning the probability that a firm will lose its founder CEO due to death or illness as a function of pre-treatment characteristics. The variables $Number\ of\ Pre\ Internal\ Patents\_3year$ and $Average\ Pre\ Firm\ Patent\ Quality\_3year$ as well as the variables $Acquisition\ Count\ Pre\_3year$ and $Number\ of\ Pre\ Acquired\ Patents\_3year$ are 3-year average internal innovation and firm acquisitiveness measures, respectively, computed over the 3 year period ending one year prior to the founder CEO turnover event (Year $t-3$ to Year $t-1$). All other explanatory variables are expressed as at one year prior to the CEO turnover event (Year $t-1$). All variable definitions are contained in Appendix 5. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Characteristics of treatment and control firms before the founder CEO turnover event

	Treatment (Professional CEO)	*Control* (Founder CEO)	(1)-(2)
Number of Firms	212	212	
Ln(1 + Number of Pre Internal Patents_3year)	1.04	0.97	0.07
	(1.26)	(1.16)	
Average Pre Firm Patent Quality_3year	0.96	0.87	0.09
	(0.50)	(0.52)	
Acquisition Count Pre_3year	0.46	0.52	-0.06
	(0.60)	(0.63)	
Ln(1 + Number of Pre Acquired Patents_3year)	0.19	0.18	0.01
	(0.52)	(0.67)	
Ln(Firm Age)	2.89	2.79	0.10
	(0.82)	(0.63)	
Ln(Firm Size)	4.72	4.64	0.08
	(2.33)	(2.04)	
Scaled Cash	0.17	0.20	-0.03
	(0.20)	(0.22)	
ROA	0.04	0.06	-0.02
	(0.36)	(0.31)	
Tobin's Q	2.89	2.41	0.48
	(3.69)	(2.39)	
Leverage	0.18	0.21	-0.03
	(0.19)	(0.27)	
TMT Size	5.63	5.67	-0.05
	(2.61)	(2.25)	
Scaled R&D	0.07	0.08	-0.01
	(0.10)	(0.17)	

	Treatment (Professional CEO)	*Control* (Founder CEO)	(1)-(2)
Scaled Capex	0.06	0.05	0.00
	(0.61)	(0.50)	
CEO Duality	0.83	0.75	0.08
	(0.38)	(0.44)	
Ln(CEO Age)	4.14	4.03	0.12**
	(0.21)	(0.19)	
CEO Female	0.01	0.03	-0.02
	(0.12)	(0.17)	
CEO Tenure	18.06	14.80	3.26
	(11.90)	(9.88)	
CEO Ownership	0.20	0.18	0.02
	(0.16)	(0.17)	
CEO PhD	0.10	0.13	-0.03
	(0.34)	(0.29)	
CEO MBA	0.20	0.21	-0.01
	(0.40)	(0.45)	
CEO Technical Education	0.33	0.34	-0.02
	(0.48)	(0.47)	
CEO Great Depression	0.28	0.16	0.12*
	(0.45)	(0.24)	
CEO Military	0.17	0.11	0.06
	(0.42)	(0.31)	
CEO Financial Expert	0.09	0.14	-0.05
	(0.24)	(0.36)	
Inventor CEO	0.33	0.31	0.02
	(0.47)	(0.47)	
CEO Overconfidence	0.05	0.06	-0.01
	(0.04)	(0.04)	

Panel B: Probability of departure of firm's founder CEO due to health-related reasons (Treatment = 1)

	(1) Prob(Treatment = 1)	(2) Prob(Treatment = 1)
Log(1 + Number of Pre Internal Patents_3year)	0.03	-0.05
	(0.27)	(0.31)
Average Pre Firm Patent Quality_3year	0.23	0.91
	(0.67)	(0.92)
Acquisition Count Pre_3year	0.08	-0.23
	(0.47)	(0.53)
Log(1 + Number of Pre Acquired Patents_3year)	-0.18	0.14
	(0.45)	(0.51)

Firm Age	-0.65	-1.08
	(0.77)	(0.92)
Firm Size	0.03	0.04
	(0.27)	(0.24)
Scaled Cash	0.92	0.85
	(1.15)	(1.38)
ROA	-1.70	-1.66
	(1.49)	(1.46)
Tobin's Q	0.01	0.09
	(0.08)	(0.08)
Leverage	-1.39	-1.02
	(1.18)	(1.29)
TMT Size	-0.11	-0.12
	(0.13)	(0.14)
Scaled R&D	-3.12	-3.38
	(2.84)	(2.94)
Scaled Capex	2.81	0.63
	(4.61)	(5.12)
CEO Duality	0.32	0.26
	(0.59)	(0.63)
CEO Age	3.36**	3.19**
	(1.69)	(1.62)
CEO Female	0.16	0.09
	(0.38)	(0.22)
CEO Tenure	0.07	0.09
	(0.04)	(0.07)
CEO Ownership	-0.77	-1.52
	(1.63)	(1.80)
CEO PhD		-1.38
		(1.07)
CEO MBA		-1.83
		(1.71)
CEO Technical Education		-0.12
		(0.74)
CEO Great Depression		0.72
		(0.90)
CEO Military		-1.04
		(0.75)
CEO Financial Expert		-0.90
		(0.83)
Inventor CEO		-0.58
		(0.67)
CEO Overconfidence		0.04
		(0.09)
Observations	424	424
Time FEs	Yes	Yes
Pseudo R^2	0.13	0.14

Table 2: Effect of exogenous founder-to-professional CEO turnovers on internal innovation

This table reports the difference-in-differences tests that examine the impact of founder CEOs on internally generated innovative output vis-à-vis professional CEOs. The dependent variables in column (1), (2) and (3) are the log of one plus the number of internally generated patents, the average scaled quality of a firm's internally developed patents and R&D expenses scaled by the book value of assets respectively. The unit of observation is a firm-year. The indicator variable *Post Founder CEO* takes the value of one if a firm's founder has relinquished the CEO position due to death or illness and has been replaced by a new non-founder/professional CEO in a given year, and zero otherwise. *Other Firm characteristics* and *Other CEO characteristics* outlined in Table 1 are included in the estimation but unreported for brevity. Other Firm Characteristics included as control variables are *Firm Age*, *Firm Size*, *Scaled Cash*, *ROA*, *Tobin's Q*, *Scaled R&D* and *Scaled Capex* (see Appendix 5 for definitions). Other CEO Characteristics included as control variables are *CEO Duality*, *CEO Age*, *CEO Female*, *CEO Tenure*, *CEO Ownership*, *CEO PhD*, *CEO MBA*, *CEO Technical Education*, *CEO Great Depression*, *CEO Military*, *CEO Financial Expert*, *Inventor CEO* and *CEO Overconfidence* (see Appendix 5 for definitions). Founder CEO turnover event dates in the sample correspond to the period 1981-2011. The standard errors are clustered at firm-year level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

	(1) Log(1 + Number of Internal Patents)	(2) Average Firm Patent Quality	(3) Scaled R&D
Post Founder CEO	-0.10**	0.02	-0.01
	(0.04)	(0.06)	(0.03)
Other Firm characteristics	Yes	Yes	Yes
Other CEO characteristics	Yes	Yes	Yes
Observations	3,903	3,903	3,849
Number of Firms	424	424	424
Firm FEs	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes
Adjusted R^2	0.23	0.17	0.21

Table 3: Internal innovation - pre-treatment trends and reversals

This table investigates the pre-treatment trends and post-treatment reversals between the treated and control group. The dummy variables *Year -2*, *Year -1*, *Year 0*, *Year +1*, *Year +2*, *Year +3*, *Year +4 and afterward* indicate the year relative to the exogenous founder-to-professional CEO turnover event. For example, the *Year +2* dummy variable takes the value of one if it is two years after the founder CEO turnover event, and zero otherwise. The dependent variables in column (1) and (2) are the log of one plus the number of internally generated patents and the average scaled quality of a firm's internally developed patents respectively. The unit of observation is a firm-year. *Other Firm characteristics* and *Other CEO characteristics* outlined in Table 1 are included in the estimation but unreported for brevity. Other Firm Characteristics included as control variables are *Firm Age*, *Firm Size*, *Scaled Cash*, *ROA*, *Tobin's Q*, *Scaled R&D* and *Scaled Capex* (see Appendix 5 for definitions). Other CEO Characteristics included as control variables are *CEO Duality*, *CEO Age*, *CEO Female*, *CEO Tenure*, *CEO Ownership*, *CEO PhD*, *CEO MBA*, *CEO Technical Education*, *CEO Great Depression*, *CEO Military*, *CEO Financial Expert*, *Inventor CEO* and *CEO Overconfidence* (see Appendix 5 for definitions). Founder CEO turnover event dates in the sample correspond to the period 1981-2011. The standard errors are clustered at firm-year level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

	(1) Log(1 + Number of Internal Patents)	(2) Average Firm Patent Quality
Year -2	-0.03	-0.04
	(0.04)	(0.06)
Year -1	0.01	-0.03
	(0.03)	(0.05)
Year 0 (founder CEO turnover year)	-0.01	0.00
	(0.02)	(0.05)
Year +1	-0.02	-0.01
	(0.05)	(0.06)
Year +2	-0.05	0.02
	(0.04)	(0.07)
Year +3	-0.11**	-0.01
	(0.05)	(0.07)
Year +4 and after	-0.15***	-0.03
	(0.05)	(0.08)
Other Firm characteristics	Yes	Yes
Other CEO characteristics	Yes	Yes
Observations	3,903	3,903
Number of Firms	424	424
Firm FEs	Yes	Yes
Time FEs	Yes	Yes
Adjusted R^2	0.31	0.26

Table 4: Effect of exogenous founder-to-professional CEO turnovers on external investment

This table reports the difference-in-differences tests that examine the impact of founder CEOs on external investment policy vis-à-vis professional CEOs. The dependent variables in column (1), (2) and (3) are the count of the number of acquisitions per firm-year, the sum of acquisition prices paid scaled by firm market capitalization and the log of one plus the number of patents acquired from external entities respectively. The unit of observation is a firm-year. The indicator variable *Post Founder CEO* takes the value of one if a firm's founder has relinquished the CEO position due to death or illness and has been replaced by a new non-founder/professional CEO in a given year, and zero otherwise. *Other Firm characteristics* and *Other CEO characteristics* outlined in Table 1 are included in the estimation but unreported for brevity. Other Firm Characteristics included as control variables are *Firm Age*, *Firm Size*, *Scaled Cash*, *ROA*, *Tobin's Q*, *Scaled R&D* and *Scaled Capex* (see Appendix 5 for definitions). Other CEO Characteristics included as control variables are *CEO Duality*, *CEO Age*, *CEO Female*, *CEO Tenure*, *CEO Ownership*, *CEO PhD*, *CEO MBA*, *CEO Technical Education*, *CEO Great Depression*, *CEO Military*, *CEO Financial Expert*, *Inventor CEO* and *CEO Overconfidence* (see Appendix 5 for definitions). Founder CEO turnover event dates in the sample correspond to the period 1981-2011. The standard errors are clustered at firm-year level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

	(1) Acquisition Count	(2) Acquisition Ratio	(3) Log(1 + Number of Acquired Patents)
Post Founder CEO	0.30** (0.13)	0.02* (0.01)	0.09** (0.04)
Other Firm characteristics	Yes	Yes	Yes
Other CEO characteristics	Yes	Yes	Yes
Observations	3,849	1,875	3,903
Number of Firms	424	424	424
Firm FEs	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes
Adjusted R^2	0.17	0.18	0.20

Table 5: Effect of exogenous CEO turnovers on corporate leverage and management approach

This table reports the difference-in-differences tests that examine the impact of founder CEOs on corporate leverage and the structure of executive management teams compared to professional CEOs. The dependent variable in column (1) is the firm's leverage ratio. The dependent variables in columns (2) and (3) are the size of the firm's executive/top management team (TMT) and the number of executive officer departures in a given year respectively. The unit of observation is a firm-year. The indicator variable *Post Founder CEO* takes the value of one if a firm's founder has relinquished the CEO position due to death or illness and has been replaced by a new non-founder/professional CEO in a given year, and zero otherwise. *Other Firm characteristics* and *Other CEO characteristics* outlined in Table 1 are included in the estimation but unreported for brevity. Other Firm Characteristics included as control variables are *Firm Age*, *Firm Size*, *Scaled Cash*, *ROA*, *Tobin's Q*, *Scaled R&D* and *Scaled Capex* (see Appendix 5 for definitions). Other CEO Characteristics included as control variables are *CEO Duality*, *CEO Age*, *CEO Female*, *CEO Tenure*, *CEO Ownership*, *CEO PhD*, *CEO MBA*, *CEO Technical Education*, *CEO Great Depression*, *CEO Military*, *CEO Financial Expert*, *Inventor CEO* and *CEO Overconfidence* (see Appendix 5 for definitions). Founder CEO turnover event dates in the sample correspond to the period 1981-2011. The standard errors are clustered at firm-year level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

	(1) Leverage	(2) TMT Size	(3) TMT Turnover
Post Founder CEO	0.12**	0.69**	-0.55**
	(0.06)	(0.30)	(0.27)
Other Firm characteristics	Yes	Yes	Yes
Other CEO characteristics	Yes	Yes	Yes
Observations	3,849	3,849	3,849
Number of Firms	424	424	424
Firm FEs	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes
Adjusted R^2	0.28	0.20	0.25

Table 6: Effect of exogenous founder-to-professional CEO turnovers on firm value

This table reports the difference-in-differences tests that examine the impact of founder CEOs on firm operating performance and firm value vis-à-vis professional CEOs. The dependent variables in columns (1) and (2) are return on assets and Tobin's Q respectively. The unit of observation is a firm-year. The indicator variable *Post Founder CEO* takes the value of one if a firm's founder has relinquished the CEO position due to death or illness and has been replaced by a new non-founder/professional CEO in a given year, and zero otherwise. *Other Firm characteristics* and *Other CEO characteristics* outlined in Table 1 are included in the estimation but unreported for brevity. Other Firm Characteristics included as control variables are *Firm Age*, *Firm Size*, *Scaled Cash*, *ROA*, *Tobin's Q*, *Scaled R&D* and *Scaled Capex* (see Appendix 5 for definitions). Other CEO Characteristics included as control variables are *CEO Duality*, *CEO Age*, *CEO Female*, *CEO Tenure*, *CEO Ownership*, *CEO PhD*, *CEO MBA*, *CEO Technical Education*, *CEO Great Depression*, *CEO Military*, *CEO Financial Expert*, *Inventor CEO* and *CEO Overconfidence* (see Appendix 5 for definitions). Founder CEO turnover event dates in the sample correspond to the period 1981-2011. The standard errors are clustered at firm-year level. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

	(1) ROA	(2) Tobin's Q
Post Founder CEO	0.03	-0.39
	(0.05)	(0.59)
Other Firm characteristics	Yes	Yes
Other CEO characteristics	Yes	Yes
Observations	3,849	3,849
Number of Firms	424	424
Firm FEs	Yes	Yes
Time FEs	Yes	Yes
Adjusted R^2	0.21	0.28

Chapter 3:
Innovation Search Strategy and Predictable Returns

3.1 INTRODUCTION

A firm's innovative output contains information that is useful in the evaluation of its future cash flows. However, because of the intangible and highly uncertain nature of innovation, investors may have difficulty processing this information when assessing the value of the firm (Jensen 1993; Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2013). This occurs even if a firm patents its inventions, thereby disclosing its technology and innovation strategy to the world.

Here we ask whether investors can accurately value the innovation search strategy of a firm, characterizing this strategy as a choice between the exploration of new capabilities and the exploitation of a firm's extant competencies (March 1991, Manso 2011). Firms following an exploration strategy seek novel technologies and approaches that are new to the firm while those following an exploitation strategy, in contrast, "stick to their knitting" and refine currently successful and previously patented approaches. Exploration requires search that is distant from the firm's current knowledge and capabilities while exploitation relies on local search of a firm's existing competencies.

Many studies show that, due to limited investor attention, prices do not fully incorporate all available information (e.g. Klibanof, Lamont, and Wizman, 1998; Huberman and Regev, 2001; Barber and Odean, 2008; Cohen and Frazzini, 2008; DellaVigna and Pollet, 2009; Hirshleifer, Lin, and Teoh, 2009, Hou, Peng, and Xiong, 2009, Da, Engelberg, and Gao, 2011; Da, Gurun, and Warachka, 2011; Da and Warachka, 2011; Cohen and Lou, 2012; and Li and Yu, 2012). Recent work has illustrated this challenge for predicting the impact of innovation information in the form of patent grants (Hirshleifer et al., 2013; Cohen et al., 2013); here we propose two specific mechanisms that could lead investors to under value exploitation strategies. The first mechanism is cognitive; investors could display an inherent psychological bias towards interpreting salient information. The second mechanism is strategic; firms could direct investor attention towards significant technological advances, particularly if those advances occur outside of a firm's previously known research trajectory.

The psychology literature has historically suggested that people focus on salient and vivid information, especially when facing complex problems (Fiske and Taylor, 1991, Song and Schwartz, 2010). More recent neuroscience research has established a consistent preference for novelty when processing information and shown that the neurological structures of novelty recognition and reward are linked (Bunzeck et al. 2011). Expected novelty is also remembered more strongly (Whitman et al. 2007). In contrast, investors may devote insufficient time to understanding the incremental economic significance of additional patents granted in technological areas that the firm and its investors are already familiar with. By definition, breakthroughs and new trajectories are rare, making it easier to focus on them, particularly in a complex and uncertain environment. As a result, investors may overlook the potentially significant value generated by typically more process-oriented and incremental patents in order to focus on different and more exciting inventions (Banbury and Mitchell, 1995; Hult, 2014). In

other words, investors may ignore patents which fill in and solidify a previously known research trajectory in favor of patents which open up new trajectories.[36]

Independent of cognitive processes, innovative firms are also more likely to publicize the granting of patents that are considerably different from the firm's current patent portfolio (Kogan, Papanikolaou, Seru and Stoffman, 2017). Assuming that firms are not trying to hide their innovative successes, they are more likely to report patenting in a new technology area, relative to additional patents in a previously patented area. Firms are more likely to report significant advances and breakthroughs in their press and 10-K releases in an effort to educate investors on the success of its long-term growth strategy. In addition to fulfilling legal requirements, such announcements are usually intended to buoy investor confidence and stock prices (relative, for example, to the 2^{nd}, 3^{rd}, or 4^{th} patent in a developing area). The firm is even more likely to publicize such grants if it has an explicit diversification strategy, as patent grants in fields not previously patented in are credible initial evidence that the strategy is working. Thus, the relatively lower amount of information provided by firms about the future implications of their exploitative activities may further compound the effect of investors' existing bias towards understanding a firm's relatively different or unusual inventions.

These two consistent mechanisms imply that investors will pay more attention to explorative patents than exploitative patents. Therefore, we expect that information about firms engaged in exploration will be quickly incorporated into prices, while information about firms engaged in exploitation takes time to be incorporated into prices. We are thus more likely to find return predictability among stocks that focus on exploitation.

In order to test our conjectures, we first develop two alternative measures that distinguish whether a firm in any given year is relatively more focused on exploitation of the firm's existing known technologies versus exploration of newer technologies. First, we introduce a new measure called $Internal\ Search\ Proximity$ which examines the degree of overlap in terms of technology classes between patents granted to the firm in year t and the existing patent portfolio held by the *same* firm up to year $t-1$. A firm that focuses on exploitation will have substantial overlap in technology classes, while a firm that focuses on exploration will have relatively little overlap in technology classes. Second, we adapt the "explorative" patent definition developed by the recent innovation literature that classifies patents as being exploratory in nature if the majority of the patents it cites as prior art represent new knowledge to the firm. We use this to develop a firm's $Exploitative\ Patent\ Ratio$ which classifies firms as being focused on exploration/(exploitation) if a relatively greater/(lesser) proportion of their newly granted patents utilize new knowledge sources. As a result, a firm's *Exploitation Search Focus* score either equals their $Internal\ Search\ Proximity$ or their $Exploitative\ Patent\ Ratio$ value such that firms with high exploitation search focus scores are classified as pursuing an exploitation innovative search strategy and vice versa.

We then examine whether differences in firm innovative search focus contains predictive information about a firm's future profitability and operating cash flows. We conduct annual Fama and Macbeth (1973) cross-sectional regressions of an individual firm's future profitability, defined as either one year-ahead return on assets (*ROA*) or one year-ahead operating cash flow (*OCF*), on a firm's exploitation search focus score as well as a vector of other control variables. We find a significantly positive relationship between a firm's exploitation search focus and

[36] This mechanism is analogous to behavioral explanations of the value premium (see e.g. Lakonishok, Shleifer, and Vishny, 1994), according to which growth/glamour stocks are overvalued because investors are over-excited about their future earnings growth.

future ROA and OCF in all specifications. High exploitation firms tend to generate superior subsequent operating performance (at least in the near to intermediate term) relative to high exploration firms, consistent with the idea that incremental innovation produces more immediate cash flows relative to higher risk exploration projects with longer term expected payoffs.

We next investigate the extent to which the market accurately incorporates any such predictability into its earnings expectations, using consensus analyst forecasts as proxies for market expectations. If the market fails to fully understand the positive impact of exploitative patents on future firm profitability, then we might observe more positive "earnings surprises" for exploitation-focused firms which may in turn result in these firms generating abnormally high future stock returns. We conduct quarterly Fama and Macbeth (1973) cross-sectional regressions of realized earnings surprise in each of the four quarters in year t+1 on exploitation search focus in year t and other firm-specific control variables. Interestingly, we find that firms currently focused on exploitation tend to significantly outperform the market's near-term earnings expectations. This implies that high exploitation firms not only tend to generate superior subsequent operating performance relative to high exploration firms but that the market does not seem to fully factor the positive economic value generated by exploitative patents into its earnings expectations for these firms. As such, we identify a potential channel through which certain innovative firms may be systematically undervalued by the market.

We finally examine whether the direction of a firm's innovative search efforts systematically predicts stock returns. Using a portfolio sort methodology, we find that firms with high exploitation search focus scores (high exploitation firms) are undervalued relative to high exploration firms and that this return differential is incremental to standard risk and innovation-based pricing factors examined in the prior literature. Using Fama-Macbeth (1973) cross-sectional regressions, we confirm that the return predictive ability of our relative innovative search focus measure is distinct from and robust to the inclusion of other commonly used return predictors and innovation-based variables.

It is a widely held view that stock market pressure hampers innovation (Stein 1989; Ferreira, Silva, and Manso 2013), for example, through the impact of short-term earnings pressures. Our results provide a more nuanced view, as the stock market effect on innovation depends on the type of innovation. If as we show markets underestimate the significant value generated by exploitative innovation, then exploratory innovation rather than exploitative innovation becomes more attractive to firms, conditional on the amount of resources allocated to research and development. The lower cost of capital associated with exploration makes it more attractive for firms to pursue this type of innovation when compared to exploitation.

Our earnings surprise and return predictability results also have implications for optimal firm financing policy and corporate disclosure policy in relation to a firm's innovative activities. With respect to firm financing policy, the undervaluation of high exploitation firms relative to high exploration firms by public equity markets will likely drive managers of exploitation-focused firms to strongly prefer the use of cash and debt to fund the firm's innovative investments. With respect to corporate disclosure policy, our results emphasize the need for firms pursuing an exploitative innovation search strategy to provide greater investor guidance as to the beneficial earnings impact, particularly in the short-term, of exploitative patents.

Our study contributes to the growing literature on the relationship between corporate innovative activities and financial markets. In particular, we introduce two new patent-based measures to capture the theoretical distinction between 'exploration' and 'exploitation' in corporate innovative search strategy (March, 1991, and Manso, 2011). Our results expand on the

recent findings that investors tend to undervalue firms that: (a) invest heavily in R&D and have exhibited historical success in converting R&D investment into sales (Cohen et al., 2013); (b) are efficient in translating R&D expenditure into future patents (Hirshleifer et al., 2013) and (c) produce patents that are relatively more "original" compared to *all* other patented innovation, as proxied by the diversity of the technological classes cited (Hirshleifer et al., 2017). While these papers illustrate investors' difficulty in *comparing distinct firms* across innovation metrics, such as historical capacity or current originality of their patents, our findings highlight the additional difficulty that investors encounter when interpreting the incremental economic significance of a firm's current innovative output relative to the past innovative output of the *same firm*.

Building on recent literature, we argue that the trade-off between exploration and exploitation that firms face is theoretically and empirically distinct from whether firms patent original or unoriginal innovation. Firms may patent a highly original (unoriginal) innovation while following existing (new) research trajectories, which is evidenced by very low correlations of our *Exploitation Search Focus* measure with previously studied innovation-related measures such as innovative efficiency (Hirshleifer, Hsu, and Li 2013) and innovative originality (Hirshleifer et al., 2017). We find that investors tend to overlook the potentially significant value generated by exploitative patents that build on the firm's existing knowledge base. This is not inconsistent with an undervaluation of original patents (Hirshleifer et al., 2017), as it is might well be those original technological advances that are exploited to appropriate the full value of an invention. Our findings suggest that exploration and originality are distinct concepts of a more nuanced view on innovation, and that an individual firm's *internal* focus on exploitation versus exploratory innovation contains independent value-relevant information that are more effective than the market would expect.

3.2 DATA AND SAMPLE DESCRIPTION

We discuss this study's data sources in Section 3.2.1 while in Section 3.2.2 we outline the construction of our two empirical measures used to classify firms as having a relatively greater focus on exploitative or explorative innovation. We present key summary statistics and variable correlations in Section 3.2.3.

3.2.1 Data sources

Our empirical analysis is based on the joint availability of firm level data for publicly traded U.S. firms in the Compustat, CRSP (Center for Research in Security Prices) and NBER patent databases. We use stock return data from CRSP and obtain accounting data from Compustat. Our initial sample consists of all domestic common shares trading on the NYSE, AMEX or NASDAQ with sufficient accounting and returns data, excluding firms with negative book value of equity and financial firms with four-digit Standard Industrial Classification (SIC) codes between 6000 and 6999. Following Fama and French (1993), we exclude closed-end funds, trusts, American Depositary Receipts (ADRs), real estate investment trusts and units of beneficial interest. Following Hirshleifer et al. (2013), we require firms to be listed in Compustat for two years before including them in our sample in order to mitigate backfilling bias.

Patent-related data is sourced from both the NBER patent database, originally developed by Hall, Jaffe and Trajtenberg (2001), as well as the Fung Institute's public patent database at the University of California, Berkeley (Balsmeier et al. 2016). The NBER patent database contains various details on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO)

between January 1976 and December 2006, including patent assignee identifiers that facilitate the matching of USPTO patent information with firm level data contained in the Compustat and CRSP databases. The information in the NBER database is then supplemented with technology class data from the Fung Institute's database. As discussed more extensively below, since many of the patent-based variables employed by this study require the examination of at least five years of historical patent information for each sample year, our sample period begins in 1981 and ends in 2006. For some of our tests, we also obtain institutional ownership data from the Thomson Reuters Institutional (13F) Holdings database and analyst estimates data from the Institutional Brokers' Estimate System (I/B/E/S).

3.2.2 Patent-based measures of relative innovative search focus

In order to distinguish firms in any given year based on their relative focus on exploitation of existing known technologies versus exploration of newer technologies (otherwise referred to as a firm's level of *exploitation search focus*), we use two alternative empirical measures that draw on two distinct sources of patent-level information.

First, we develop a novel measure $Internal\ Search\ Proximity$ which examines the degree of overlap between patents granted to the firm in year t and the existing patent portfolio held by the same firm up to year $t-1$. In particular, we employ the following variant of the Jaffe (1989) technological proximity measure to estimate the "closeness" in technological space of firm i's new patents in year t[37] and its depreciation-adjusted[38] pre-existing patent stock at time $t-1$ using patent counts in different USPTO three-digit technology classes k:

$$Internal\ Search\ Proximity_{i,t} = \frac{\sum_{k=1}^{K} f_{i,k,t} f_{i,k,t-1}}{(\sum_{k=1}^{K} f_{i,k,t}^2)^{\frac{1}{2}} (\sum_{k=1}^{K} f_{i,k,t-1}^2)^{\frac{1}{2}}} \quad (1)$$

where $f_{i,k,t}$ is the fraction of patents granted to firm i in year t that are in technology class k such that the vector $f_{i,t} = (f_{i,1,t} \dots f_{i,K,t})$ locates the firm's year t patenting activity in K-dimensional technology space. $Internal\ Search\ Proximity_{i,t}$ will be zero for a given firm year when there is no overlap in firm innovative output between time $t-1$ and time t while $Internal\ Search\ Proximity_{i,t}$ will equal one when the distribution of firm i's patents obtained this year is identical to patents accumulated in previous years. Therefore, we classify firms as being relatively more focused on exploration/(exploitation) when they have low/(high) values of $Internal\ Search\ Proximity_{i,t}$.

Second, to further enhance and validate the robustness of our identification of firms pursuing exploitation versus exploration innovative search strategies, we adopt an alternative measure used in many recent innovation-related studies such as Ma (2016), Brav et al. (2016) and Lin et al. (2016). Specifically, we define "new cite ratio" and "exploitativeness" which measure the percentage of new knowledge used in a firm's current innovative output. New knowledge is identified by patent citations to patents that have not been previously developed or cited by the firm. In particular, we first define firm i's existing knowledge in year t as all patents either produced by firm i or that were cited by firm i's patents up to year $t-1$. The "new cite ratio" of

[37] When computing *Internal Search Proximity* measures for each firm, we only use patents initially granted to the firm itself (since these patents are internally generated based on the firm's R&D activities). In robustness tests, we also include patents acquired by the firm in our calculations and find qualitatively similar results.

[38] Following studies such as Hall, Jaffe and Trajtenberg (2005), we apply a 15% depreciation rate to a firm's past patent stock when calculating our relative innovative search focus measure. Our results are almost identical if we use a 0% or 20% depreciation rate instead.

a patent is calculated as the total number of citations made to new knowledge divided by the total number of citations made by the patent. Following the prior literature, a patent is flagged as "explorative" if at least 80% of its citations are based on new knowledge (new cite ratio $\geq$ 80%). We can then transform these patent-level measures to the firm-year level by creating the "explorative patent ratio", defined as the total number of firm i's patents granted in year t that are classed as "explorative" divided by the total number of patents granted to firm i in year t. We can use the "explorative patent ratio" to create its corollary the $Exploitative\ Patent\ Ratio_{i,t}$, defined as one minus firm i's "explorative patent ratio" in year t. As a result, we classify firms as being relatively more focused on exploration/(exploitation) when they have a low/(high) value for their $Exploitative\ Patent\ Ratio_{i,t}$.

One particularly notable aspect of our relative innovative search focus measures is that, in order to assess the *direction* of a firm's dynamic innovative search strategy over time, we need information about both the firm's current *and* past innovative activities. For example, for our $Internal\ Search\ Proximity_{i,t}$ measure, we can only identify firms as being relatively more focused on exploration or exploitation by knowing about the technological classes in which the firm has previously been patenting. Similarly, we can only classify firms who are relatively more focused on exploiting existing knowledge as opposed to exploring new knowledge using the $Exploitative\ Patent\ Ratio_{i,t}$ once we identify the focal firm's set of "existing knowledge." As a result, we only include firms that are granted at least one new patent in year t in our subsequent analysis.

Although this requirement results in a smaller overall sample compared to some other innovation-related studies,[39] our goal of identifying a firm's potentially dynamic innovation strategy means that we require access to objective patent-based information about a firm's current *and* past innovative activities. Furthermore, we believe that restricting research attention to the sample of more actively patenting firms who are more focused on conducting innovative activities as part of their core business operations is beneficial for interpreting our subsequent results and understanding the nature of the relationship between innovation search strategies and public equity markets. For example, we avoid imposing strong assumptions about whether firms with no current patents are engaged in explorative or exploitative innovation search strategies in the pursuit of obtaining the maximum possible sample size. Combined with the fact that our focus on actively patenting firms still results in our study examining publicly traded U.S. companies who comprise over 50% of total U.S. market equity (comparable to the 55% of total U.S. market equity covered by the innovative efficiency measures in Hirshleifer et al., 2013) and the fact that we use two alternative measures ($Internal\ Search\ Proximity$ and $Exploitative\ Patent\ Ratio$) that rely on two distinct sources of patent-based information (patent technology class and patent back citations, respectively) to classify firms as being relatively more focused on innovative exploitation or exploration, we believe that our results robustly identify the relationship between firm innovative search strategy and stock market valuations as well as demonstrate a high level of economic relevance.

3.2.3 Sample composition and summary statistics

Table 1 reports summary statistics of the three exploitation search focus portfolios (based on $Internal\ Search\ Proximity$ or $Exploitative\ Patent\ Ratio$) and the correlation between a

[39] For example, Hirshleifer et al. (2017) calculate their firm-year innovative originality measure using an average of all patents granted to the firm over the previous five years.

firm's exploitation search focus measure and other firm characteristics. In particular, we form three portfolios at the end of June of year t based on the 30th and 70th percentiles of firm exploitative search focus scores measured in year $t-1$.

Panel A reports the average annual number of firms in each portfolio and the median value of various firm characteristics within these portfolios, where all characteristics are for the year prior to the ranking year except for size, momentum, illiquidity, idiosyncratic volatility and total skewness (which are measured at the end of June of the ranking year). These characteristics include size (measured as the natural log of market capitalization), the year-end book-to-market equity ratio (*BTM*), momentum (calculated as the prior six month stock return with a one month gap between the holding period and the current month following Hou, Peng and Xiong, 2009), *Patent*s (defined as patents granted in year $t-1$ divided by lagged total assets), *Capex* (calculated as capital expenditure divided by lagged total assets), *R&D* (measured as R&D expenditures scaled by lagged total assets), illiquidity (defined as the absolute monthly stock return divided by monthly dollar trading volume in June of year t as in Amihud, 2002), Leverage (*LEV*, computed as total debt divided by lagged total assets), net stock issues (*NS*, defined as the change in the natural log of split-adjusted shares outstanding in year $t-1$), institutional ownership (*Inst. Own*, calculated as the fraction of firm shares held by institutional investors), idiosyncratic volatility (*IV*, measured at the end of June of year t as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months following Hirshleifer, Hsu and Li, 2017), total skewness (*SKEW*, calculated at the end of June of year t using daily stock returns over the previous 12 months), innovative efficiency (*IE*, defined as, "adjusted patent citations scaled by R&D expenses," per Hirshleifer et al., 2013) and innovative originality (*IO*, defined as the average score of a firm's patents' originality scores, where originality is "the number of unique technological classes (both primary and secondary classes) assigned to the patents cited by the focal patent" over the past five years following Hirshleifer et al., 2017).

For example, across the 306, 406 and 306 firms that are on average in the low, middle and high exploitation search focus portfolios each year (based on $Internal\ Search\ Proximity$) respectively, the median market capitalization of firms in the low, middle and high relative innovative search focus portfolios is \$146 million, \$411 million and \$530 million respectively. As such, our sample is concentrated in relatively larger firms that comprise an economically meaningful 50% of total US market equity. Furthermore, there is significant variation in the exploitation search focus measures across the various portfolios. In particular, the median exploitation search focus measure in the low group based on $Internal\ Search\ Proximity$ and $Exploitative\ Patent\ Ratio$ is zero in both cases while the median value in the high group is 0.94 and 0.88 respectively. We also find that firms with higher exploitation search focus scores have higher R&D intensity, higher innovative efficiency based on citations and a higher patent-to-total assets ratio.

Interestingly, there is some evidence to suggest that there exists a positive univariate relationship between a firm's current focus on exploitation and future operating performance. In particular, the high exploitation search focus portfolio exhibits a higher return on assets (measured as income before extraordinary items plus interest expenses scaled by lagged total assets) and higher operating cash flow (calculated as income before extraordinary items plus depreciation and minus changes in working capital scaled by lagged total assets) in the year following portfolio formation. We examine this relationship in greater detail in Section 3.3.

In Panel B of Table 1 we report the pairwise Pearson correlation coefficients among our exploitation search focus measures and other firm characteristics. In general, our two exploitation search focus measures do not strongly correlate with the firm characteristics shown in Panel A, ranging from -0.13 with BTM to 0.13 with size. However, there is very strong positive correlation of 0.51 between *Internal Search Proximity* and *Exploitative Patent Ratio* despite the fact that the two measures are constructed using two quite distinct sources of patent-level information (a patent's designated primary technology class and the back citations made by a particular patent respectively). The fact that one can use two distinct sources of information about individual patents to construct firm-level patent portfolio measures that reach a similar conclusion about whether a firm is pursuing an exploitation or exploration innovative search strategy provides additional comfort as to the robustness of our approach to classifying firms based on their innovative search strategies.

The correlation of the two exploitation search focus measures with previously used measures IE and IO is relatively low with *Internal Search Proximity* having a correlation with IE and IO of 0.02 and -0.01, respectively; *Exploitative Patent Ratio* has a correlation with IE and IO of 0.03 and 0.10, respectively. This indicates that our measures for distinguishing firms' relative focus on exploitation versus exploration remain distinct from other previously examined innovation-based return predictors and thus have the potential to contain independent value-relevant information. For example, a firm's patent portfolio may have a high innovative originality score and still be following an exploitative innovation search strategy because the citations made by the firm's current patents are to its own existing stock of patents and/or prior knowledge. Similarly, a firm with a low originality score in a given year may well be pursuing an explorative search strategy through the acquisition of new knowledge contained in patents not previously worked on or utilized by the firm's inventors and by patenting in new technology classes. These exploration strategies could be orthogonal to the diversity of technology class assignment (as reflected in innovative originality, which counts the number of USPTO classes that are assigned to a patent). In related research, Manso et al. (2016) find that the commonly used "innovative originality" measure developed by Hall et al. (2001) does *not* load on either the 'exploitation' or 'exploration' component in their principal components analysis, further indicating the distinctiveness of our exploitation search focus measures from innovation-related variables developed in the prior literature. Nevertheless, for robustness purposes, Appendix 1 includes both IE and IO as controls in all subsequent regression analysis and we find that both of our exploitation search focus measures continue to contain meaningfully incremental value-relevant information.

3.3 INNOVATIVE SEARCH FOCUS AND FUTURE OPERATING PERFORMANCE

We first examine whether differences in firm innovative search focus contains predictive information about a firm's future profitability and operating cash flows. We then investigate the extent to which the market accurately incorporates any such predictability into its earnings expectations.

3.3.1 Relative innovative search focus and future operating performance

Following Fama and French (2000), we conduct the following annual Fama and Macbeth (1973) cross-sectional regressions of an individual firm's future profitability, defined as either

one year-ahead return on assets (*ROA*) or one year-ahead operating cash flow (*OCF*), on a firm's exploitation search focus score as well as a vector of other control variables (*X*):

$$OP_{i,t+1} = \alpha + \beta Exploitation\ Search\ Focus + \gamma X_{i,t} + \sum_{j=1}^{48} \delta_j Industry_j + \varepsilon_{i,t} \quad (2)$$

Following the prior literature, we include a variety of control variables that have been found to be significant predictors of future operating performance. We first control for current firm profitability to accommodate the documented persistence in operating performance (Gu, 2005) as well as the change in firm profitability in order to account for mean reversion in future operating performance (Fama and French, 2000). We also follow Pandit, Wasley and Zach (2011) and control for the current levels of R&D expenditure, capital expenditure, market-to-book assets and patent stock.[40] All regressions include Fama and French (1997) 48 industry fixed effects while all variables are winsorized at the 1% and 99% level to mitigate the effect of outliers (Beaver and Ryan, 2000). Following Hirshleifer et al. (2013), we also standardize all independent variables to zero mean and one standard deviation.

Table 2 reports the time series average slopes and intercepts as well as the corresponding *t*-statistics (which incorporate a Newey-West correction with 12 lags to account for possible autocorrelation in the coefficient estimates) from the annual cross-sectional regressions specified in equation (2). We first observe that there exists a significantly positive relationship between a firm's exploitative search focus and future ROA and OCF in all specifications. For example, a one standard deviation increase in a firm's $Internal\ Search\ Proximity$ (where higher values are interpreted as exhibiting a greater focus on exploitation) results in 0.41% (0.56%) increase in subsequent year ROA (OCF). As expected, the significantly positive (negative) coefficient on prior year operating performance (change in operating performance) confirms the existence of both persistence and mean reversion in firm operating performance. We also find that capital expenditure (*CapEx*) is positively correlated with subsequent ROA and OCF, indicating that greater tangible investment helps to drive future profitability. Consistent with the findings in Hirshleifer et al. (2017), we observe that innovative originality (*IO*) has a positive association with subsequent ROA while *R&D* has a significantly negative relationship with next year's operating performance measures, potentially reflecting the long-term and uncertain payoffs associated with R&D investments.

3.3.2 Earnings surprise and relative innovative search focus

While the evidence in the preceding section suggests that innovative firms that are focused on the exploitation of their existing technologies (namely firms with high exploitation search focus scores) exhibit better subsequent operating performance, it is important to consider whether the market accurately incorporates this information into its earnings forecasts. On the one hand, it is possible that the operating outperformance of exploitation firms previously documented simply reflects fundamental differences in the expected timing of returns for exploitative versus exploratory innovation that is efficiently incorporated into the market's future earnings projections. Conversely, if the market fails to fully understand the positive impact of exploitative patents on future firm profitability, then we might observe more positive "earnings surprises" for exploitation-focused firms which may in turn result in these firms generating abnormally high future stock returns.

[40] In Appendix 6.1, we also include innovative efficiency (Hirshleifer et al., 2013) and innovative originality (Hirshleifer et al., 2017) as controls to facilitate comparison with prior innovation-based return predictors.

Following So (2013), we define realized quarterly earnings surprise as the difference between actual earnings per share (EPS) and the prevailing consensus EPS forecast, scaled by total assets per share. We proxy for the earnings expectations of all investors using the consensus analyst forecast from the I/B/E/S database. The consensus forecast is defined as the mean EPS forecast amongst all equity analysts that make a forecast in the last month prior to the earnings announcement (Dellavigna and Pollet, 2009).[41] The sample period for this particular empirical test only spans 1983 to 2006 because the I/B/E/S database only started systematically recording quarterly EPS forecasts from the beginning of fiscal year 1983.

In order to examine the multivariate relationship between a firm's exploitation search focus and future earnings surprises, we conduct quarterly Fama and Macbeth (1973) cross-sectional regressions of realized earnings surprise in each of the four quarters in year t+1 on exploitation search focus in year t and other firm-specific control variables. We initially control for the following firm-specific characteristics: last quarter's realized earnings surprise for firm i (*Lagged ES*) and the change in earnings surprise between the prior two quarters (ΔES) to account for the persistence and mean reversion in future firm profitability (So, 2013), *Accruals* (defined as total accruals in year t scaled by lagged total assets following Sloan, 1996), return on equity (*ROE*, calculated as income before extraordinary items in year t divided by lagged total equity) and an indicator for whether the consensus analyst EPS forecast for that quarter is negative (*negative EPS*) per Fama and French (2006). In subsequent specifications we also control for *BTM*, *Momentum* (defined as the prior six month returns prior to the relevant earnings announcement), *R&D*, *CapEx* and *Patents*.[42] All regressions include Fama and French (1997) 48 industry fixed effects while all variables are winsorized at the 1% and 99% level and standardized to have zero mean and standard deviation of one.

Table 3 presents the results of these regressions. Most notably, the significantly positive coefficient on exploitation search focus using either $Internal\ Search\ Proximity$ or $Exploitative\ Patent\ Ratio$ indicates that firms currently focused on exploitation tend to outperform the market's near-term earnings expectations. In particular, high exploitation firms on average generate "unexpected" positive income in year t+1 equal to approximately 12 basis points of total firm assets. Alternatively stated, this implies that the average firm in our sample generates profits that are 3% higher than market expectations in year t+1 for each one standard deviation increase in its exploitation search focus score.

In sum, the evidence in this section implies that high exploitation firms not only tend to generate superior near-term operating performance relative to high exploration firms but that the market does not seem to fully factor the economic value generated by exploitative patents into its near-term earnings expectations for these innovative companies.

3.4 PREDICTABILITY OF RETURNS BASED ON INNOVATIVE SEARCH FOCUS

Given the documented positive relationship between a firm's relatively greater focus on exploitation innovation and future operating performance as well as the empirical evidence that sophisticated equity market analysts (and likely a positive fraction of investors) appear to

[41] In the event that an individual analyst makes multiple forecasts prior to a firm's earnings announcement, we use only the most recent forecast. The results are qualitatively similar if we use the median forecast as the consensus forecast measure.

[42] In Appendix 6.2, we also include innovative efficiency (Hirshleifer et al., 2013) and innovative originality (Hirshleifer et al., 2017) as additional control variables.

underestimate the near-term profit potential of exploitative patents, we next examine whether the direction of a firm's innovative search efforts systematically predicts stock returns using both portfolio sort and regression methodologies.

3.4.1 Portfolio tests

In this subsection, we examine the ability of the estimated direction of a firm's innovative search activities to predict portfolio returns. At the end of June of year t, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint and three groups for each innovative search dimension (low "L", middle "M" and high "H") based on the 30th and 70th percentiles of firms' exploitation search focus scores. Following Hirshleifer et al. (2013), we perform our portfolio allocations using either a firm's $Internal\ Search\ Proximity$ or $Exploitative\ Patent\ Ratio$ score in the year $t-1$ while defining size as the market value of equity at the end of June of year t. This intersection forms 6 size-innovative search dimension portfolios (i.e. S/H, B/H, S/M, B/M, S/L and B/L). We hold these portfolios over the next 12 months (July of year t to June of year $t+1$) and compute the value-weighted monthly returns of these six portfolios. We then calculate monthly size-adjusted returns of the low, middle and high portfolios using the formulas (S/L+B/L)/2 through to (S/H+B/H)/2. The hedge portfolio return is calculated as the difference in returns between the high and low exploitation search focus portfolios.

Panels A.1 and B.1 in Table 4 show that excess returns, calculated as the average monthly size-adjusted return less the one-month Treasury bill rate, increases monotonically with exploitation search focus. For example, using $Internal\ Search\ Proximity$ (see Panel A.1), the excess returns for the low, middle and high portfolios are 0.58%, 0.76% and 0.86% respectively with the return spread of 0.28% per month between the high and the low portfolio significant at the 1% level.

We next examine whether the size-adjusted returns of the innovative search dimension portfolios can be captured by standard risk factor models. In particular, we perform time-series regressions of the portfolios' excess returns on the Fama-French three factors (the market factor *MKT*, the size factor *SMB* and the value factor *HML*) as well as Carhart's (1997) momentum *MOM* factor. We also report the alphas (in percentage terms) and factor loadings estimated from other commonly used factor models as a robustness check. For example, we augment the Fama French three-factor model with the robust-minus-weak (*RMW*) profitability factor and the conservative-minus-aggressive (*CMA*) investment factor in Fama & French (2015), the innovative efficient-minus-inefficient factor *EMI* (Hirshleifer, Hsu & Li, 2013), as well as the liquidity factor *LIQ* in Pastor and Stambaugh (2003).

Table 4 shows that the risk-adjusted returns of the exploitation search focus portfolios increase monotonically with a firm's greater focus on exploitation relative to exploration. For example, the risk-adjusted monthly returns of the hedge portfolio formed using $Internal\ Search\ Proximity$ range from 0.28% to 0.40% and are significant at the 1% level. Since these portfolios are only rebalanced once a year and do not comprise small illiquid firms as shown in Table 1, these abnormal returns are unlikely to be nullified by typical trading costs.

In terms of noteworthy hedge portfolio risk factor loadings, the significantly negative SMB loading and significantly positive CMA loading are consistent with the results in Table 1 that illustrate that high exploitation firms are generally bigger and undertake higher levels of investment. The significantly negative loading on the market factor indicates that high exploitation firms have lower market risk than high exploration firms while the significantly

positive loading on the EMI factor suggests that high exploitation firms are more efficient in their R&D endeavors. This is consistent with an exploitation search strategy, which prefers risk-averse refinement of opportunities already identified by the firm, relative to the exploration of enticing but less understood possibilities. While exploration may increase the chances of a breakthrough change in a firm's innovation trajectory and long-term earnings potential, an explorative search strategy also fails more often and seems to result in a less R&D efficient search strategy on average.

We also consider the time-series variation in hedge portfolio returns over our 1982 to 2008 sample period. Figure 1 shows the return on the hedge portfolio of high exploitation minus low exploitation focused firms (using *Internal Search Proximity* and *Exploitation Patent Ratio* respectively) as well as the market factor returns (*MKT*) from 1982 to 2008 (where we annualize the observed six month returns for 1982 and 2008). There are three noteworthy observations. First, the annual returns on both hedge portfolios are positive in at least two-thirds of the sample years, have less than half the return volatility of the market factor and appear to offer a hedge against market downturns (for example, the correlation of annual returns between the *Exploitation Patent Ratio* hedge portfolio and the market factor is -0.35). Second, the ex post annual Sharpe ratio for the high-minus-low exploitation search focus portfolio compares favorably to commonly used risk factors. For example, based on the *Exploitation Patent Ratio*, the hedge portfolio's Sharpe ratio of 0.45 is above that of SMB (0.08), CMA (0.33) and HML (0.34) and is comparable to the Sharpe ratio of the market factor (0.47) and RMW (0.57). Finally, our aggregate abnormal return patterns appear to persist across our entire sample period. In particular, when we split our sample in half and compare portfolio performance, we find that hedge portfolio returns are abnormally high and statistically significant in both halves of our sample (untabulated).

To further understand our return predictability results, Figure 2 plots the alphas of the high-minus-low exploitation search focus hedge portfolio over the three years post portfolio formation for the Cahart and Fama & French five-factor models. Interestingly, the market appears to fully correct the undervaluation of high exploitation firms in the first year after portfolio formation. This is consistent with the earnings surprise evidence in Section 3.3.2 whereby investors initially under-estimate the beneficial impact of exploitative patents on a firm's short-term earnings potential and then quickly incorporate this unexpected positive news into its future earnings projections. While we do not conclusively rule out the possibility of risk-based explanations for our portfolio sort results, the observed pattern of stock price correction over relatively short time periods appears to be more indicative of mispricing-based return predictability rather than risk-based return predictability, consistent with the arguments in Chamber, Jennings & Thompson (2002) and Hirshleifer et al. (2017)

Overall, these portfolio results imply that firms with high $Internal\ Search\ Proximity$ or $Exploitative\ Patent\ Ratio$ scores (high exploitation firms) are undervalued relative to high exploration firms and that this return differential is incremental to standard risk and innovation-based pricing factors examined in the prior literature.

3.4.2 Fama-Macbeth regressions

Using monthly Fama-Macbeth (1973) cross-sectional regressions, we examine the ability of a firm's innovation strategy (exploitation balanced with exploration) to predict the cross-section of stock returns. The advantage of this approach is that it allows for the inclusion of a comprehensive set of firm-level controls to ensure that the positive exploitation-return relation as

measured in the portfolio sorts in the previous section is not driven by other known return predictors or industry effects.

Following Fama and French (1992), for each month from July of year t to June of year $t+1$ we regress monthly returns of individual stocks (net of the one-month Treasury bill rate) on firms' alternative exploitation search focus measures and other control variables at year $t-1$.[43] The control variables that we include in our regression specifications, namely size, BTM, momentum, short-term reversal (*ST reversal*, defined as the previous month's stock return), CapEx, R&D, Patents, Illiquidity, ROE, Inst. Own, NS, IV and SKEW, are defined in Table 1.[44] As in section 3.4.1, we winsorize all independent variables at the 1% and 99% levels and we standardize all independent variables to have a mean of zero and a standard deviation of one.

We report the time series average slopes (in percentage terms) and the corresponding heteroscedasticity-robust *t*-statistics from the monthly cross-sectional regressions in Table 5. In all specifications, the coefficient on exploitation search focus is significantly positive, ranging from 6 to 11 basis points per month. At least in terms of short-term stock returns, this implies that firms focused on the exploitation of their existing known competencies tend to significantly outperform firms pursuing innovations in fields that are more distant from the firm's existing knowledge set.

The coefficients on the control variables are in general consistent with the prior literature, whereby firms with a higher book-to-market ratio, higher R&D intensity, lower capital intensity, higher ROA, lower net stock issuance and higher institutional ownership provide significantly higher future stock returns. Furthermore, the importance of the persistence and mean reversion in stock returns is evident in the positive coefficient on momentum and the negative coefficient on short-term reversal.

Overall, consistent with the notion that higher than expected profitability drives higher near-term stock returns, the return predictive ability of our exploitation search focus measures is distinct from and robust to the inclusion of other commonly researched return predictors and innovation-based variables as well as general industry effects.

3.5 DISCUSSION

Research on innovation - typically using patent data - has become popular in the finance literature recently (Lerner & Seru 2015). Most germane to the current results, Hirshleifer et al. (2013) illustrate how investors undervalue a firm's prior R&D productivity (as measured by patents/R&D investment) and Cohen et al. (2014) illustrate how investors undervalue a firm's proven capacity to innovate when considering the value of future R&D investment. We interpret our work as building on these arguments and results. One would expect exploitation strategies to correlate with R&D productivity and past success. If the argument for the riskiness of exploration holds, it would be surprising if an exploration search strategy proved more productive in patenting, as one would expect an increase in unsuccessful research efforts that failed to produce a patent. Similarly, if one assumes that search requires learning and adjustment of organizational routines and development processes, one would also be surprised if search resulted in immediately greater R&D productivity (it might well subsequently result in greater

[43] Using the lagged values of the independent variables ensures that all accounting and patent-based measures are fully observable to the public prior to the return estimation period (Fama and French, 1992).

[44] In Appendix 6.3, we also include innovative efficiency (IE) and innovative originality (IO) as additional explanatory variables. Our results are qualitatively unchanged.

labor or overall productivity although those are topics beyond the scope of this paper). Similarly, one should not automatically expect firms that follow exploration search strategies to be more successful, on average, than those that follow exploitation strategies. Indeed, the hope of exploration is that the strategy finds a new vein of rich payoff and that the firm can then mine those payoffs in the future with an exploitation strategy.

At some point, however, exploitation veins run out and a firm must find new opportunities. This implies that the benefits of exploitation are likely to be primarily short-term in nature while the benefits of exploration are more likely to be realized further in the future. Therefore, while we present evidence consistent with the hypothesis that the market (at least in the short-term) undervalues firms that are engaged in the exploitation of their existing technologies, it would be incorrect to characterize our results as demonstrating that exploration-focused search strategies are not beneficial for corporations to pursue.

However, our return predictability results do have implications for optimal firm financing policy and corporate disclosure policy in relation to a firm's innovative activities.

With respect to firm financing policy, the relatively short-term undervaluation of high exploitation firms relative to high exploration firms by public equity markets (see discussion in Section 3.4.1) implies that corporate executives need to adjust their mix of project financing choices depending on the type of innovation search strategy being pursued. In particular, if a firm is following an innovation exploitation search strategy, then value-maximizing firm managers will avoid issuing underpriced equity securities to fund R&D operations and instead strongly prefer the use of cash and debt to fund the firm's innovative investments. Thus, as advocated in He & Tian (2017), our results speak to the broad and relatively unexplored question of how corporate innovation affects a firm's financial performance and policies.

With respect to corporate disclosure policy, our results highlight the need for companies focusing on innovative exploitation to provide greater investor guidance as to the beneficial earnings impact, particularly in the short-term, of exploitative patents. Indeed, as shown in Section 3.3.2, even relatively sophisticated equity analysts seem to struggle to quantify the significant short-term earnings potential and thus overall value inherent in exploitative patents. Given studies such as Haggard, Martin & Pereira (2008) who find that increased corporate disclosure leads to an increase in a firm's stock price informativeness, exploitation-focused firms would appear to have the most to gain from detailing the incremental value of new patents granted within the firm's pre-existing areas of technological expertise.

Relatedly, our proposed mechanisms rely heavily on the assumption that an investor has limited attention and that s/he focuses on the impact of explorative rather than exploitative patents. One of our proposed mechanisms assumes that firms (with or without a conscious understanding of the mechanism) manipulate the focus of attention of investors, for example, by highlighting certain types of innovation. This assumption could be tested empirically, by comparing the measure of a published patent portfolio with respect to innovation strategy, relative to a firm's media strategy (for example, how often, to what extent, and for which types of patents, is the publication of a grant announced or commented upon by the firm). The effectiveness of a firm's media strategy could also be gauged, along with the technology and inventor communities' reactions, through an analysis of social media. The differences across types of innovation and how they are publicized and perceived might reveal additional mismatches in valuation and performance. This line of reasoning could be extended to a more granular level and build on recent work that predicts the value of a particular patent based on

stock market reaction (Kogan et al., 2017). It would be interesting to understand whether investors may also under-value individual patents as well as entire portfolios.

3.6 CONCLUSION

How innovation impacts a firm's future earnings is difficult to predict, particularly for investors with limited attention and bounded cognition. We focus on how accurately investors can assess the impact of a firm's internal innovation search strategy on its stock market valuation. We find that firms that exploit extant technologies close to the firm's existing technological specialties ('exploitation' focused firms) tend to generate superior subsequent near-term operating performance, relative to those that explore for new opportunities outside of the firm's existing knowledge base ('exploration' focused firms). Equity analysts do not appear to detect this, as firms currently focused on exploitation tend to significantly outperform the market's near-term earnings expectations. The market similarly fails to immediately incorporate all information about a firm's innovative search strategy. We find that firms with high exploitation search focus scores (high exploitation firms) are undervalued relative to high exploration firms and that this return differential is incremental to standard risk and innovation-based pricing factors examined in the prior literature.

Our results point to a more nuanced view of the belief that firms respond to short-term earnings pressures by underinvesting in fundamental research, possibly decreasing the number of patents, breakthroughs, and overall innovative output (Dechow and Sloan 1991; Bushee 1998). The argument is that stock market pressure hampers innovation, due to short term pressures for performance (Stein 1989; Ferreira, Manso, and Silva 2014). Our paper suggests that the market's feedback effects on innovation might depend on the type of innovation. If exploitative efforts are given overly low attention and value, firms might surprisingly be biased towards exploratory innovation rather than exploitation. This would be consistent with increased private investment in fundamental research and development (Mervis 2017).

These results also indicate the importance of firms adjusting both their capital structure choices and corporate disclosure policies to align with the firm's chosen innovative search strategy. In particular, firms pursuing an exploitation innovation search strategy may need to reduce their reliance on equity financing and/or increase their level of corporate disclosure in order to better educate investors of the significant value generated by such a search strategy.

Separately, our results have implications for the interpretation of research findings that rely on firms' patent counts as an outcome measure or explanatory variable (Lerner and Seru, 2017). Since patent portfolios that are of exploitative nature seem to be systematically undervalued, the relation between patent counts and market value based measures like Tobins' Q will be biased as well and vary according to whether the underlying portfolio reflects an exploitative or explorative strategy. In unreported regressions of patent portfolio values (based on KPSS data) on our innovation search measures, for instance, we find that the average value of a patent increases with increased focus on exploitation and declines with increased focus on exploration.

In addition, further research is needed to determine the economic value of explorative and exploitative search strategies and how investors influence that value. If, for instance, explorative efforts were positively related to socially beneficial knowledge spillovers (the social value of innovations) and negatively related to business stealing effects (Boom, Schankerman & Van Reenen, 2013; Kaplan et al. 2017), then the relative lack of attention given to exploitative innovations by investors might well turn out to be economically beneficial.

3.7 TABLES

Table 1: Summary statistics

At the end of June of year *t*, we sort firms into three groups (low, middle and high) based on the 30th and 70th percentile of our exploitation focus measures, *Internal search proximity* and *Exploitative patent ratio*, in year *t*-1 (where low and high values are classified as firms focused more on exploration and exploitation respectively). The portfolios are formed every year from 1982 to 2007. Panel A reports the average annual number of firms and pooled median characteristics of each of the three groups. *Size* is the Center for Research in Security Prices (CRSP) price per share times the number of shares outstanding at the end of June of year *t*. The book-to-market equity ratio (*BTM*) is the ratio of book equity of fiscal year ending in year *t*-1 to market equity at the end of year *t*-1. *CapEx* is capital expenditure in fiscal year *t*-1 divided by total assets at the end of year *t*-2. *R&D* is R&D expenditure divided by lagged total assets. *Patents* is the number of patents granted to the firm in year *t*-1 divided by lagged total assets. *Momentum* is the prior 6 month returns (with one month gap between the holding period and the current month). *Return on assets* (ROA) is defined as income before extraordinary items plus interest expenses scaled by lagged total assets. *Return on equity* (ROE) is defined as income before extraordinary items divided by lagged shareholder's equity. *Operating Cash Flow* (OCF) is calculated as income before extraordinary items plus depreciation and minus changes in working capital (defined as changes in current assets minus changes in current liabilities plus changes in short term debt and minus changes in cash) scaled by lagged total assets. *Net stock issues* (NS) is the change in the natural log of the split-adjusted shares outstanding. Split-adjusted shares outstanding is Compustat shares outstanding times the Compustat adjustment factor. *Institutional ownership* (Inst. Own) denotes the fraction of firm shares outstanding owned by institutional investors. *Illiquidity* is the absolute monthly stock return divided by monthly dollar trading volume in June of year *t* as in Amihud (2002). *Idiosyncratic volality* (IV) is measured at the end of June of year *t* as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months with a minimum of 31 trading days following Hirshleifer et al. (2017). *Total Skewness* (SKEW) is calculated at the end of June of year *t* using daily returns over the prior 12 months with a minimum of 31 trading days. *Innovative efficiency* (IE) is the the patent citations-based measure developed in Hirshleifer et al. (2013). *Innovative Originality* (IO) is defined as the average patent citation diversity of a firm's patents over the past five years following Hirshleifer et al. (2017). Panel B reports Pearson correlation coefficients between selected variables (*p*-values reported in parentheses).

Panel A: Firm characteristics

	Internal search proximity			Exploitative patent ratio		
Variable	Low	Middle	High	Low	Middle	High
Number of firms	306	406	306	383	322	314
Internal search proximity	0.00	0.62	0.94	0.00	0.71	0.83
Exploitative patent ratio	0.00	0.40	0.61	0.00	0.40	0.88
Size (millions of dollars)	146.3	411.3	530.0	143.8	769.4	336.0
BTM	0.49	0.49	0.42	0.52	0.46	0.42
Capex	0.05	0.05	0.05	0.05	0.05	0.05
R&D	0.03	0.04	0.06	0.03	0.05	0.05
Patents	0.01	0.02	0.03	0.01	0.02	0.02
Momentum	0.07	0.09	0.09	0.08	0.08	0.09
ROA	0.06	0.07	0.07	0.06	0.07	0.07
ROE	0.08	0.10	0.11	0.09	0.11	0.10
OCF	0.06	0.08	0.08	0.07	0.08	0.08
NS	0.01	0.01	0.01	0.01	0.01	0.01
Inst. Own	0.31	0.41	0.36	0.31	0.44	0.38
Illiquidity	0.00	0.00	0.00	0.00	0.00	0.00
IV	0.03	0.02	0.03	0.03	0.02	0.03
IE	0.03	0.18	0.24	0.04	0.17	0.29
IO	5.75	5.67	5.17	5.20	5.61	5.86

Panel B: Correlation matrix

Variable	Internal search prox.	Exploitative patent ratio	Size	BTM	Patents	R&D	ROA	IE	IO
Internal search prox.	1.00								
Exploitative patent ratio	0.51 (0.00)	1.00							
Size	0.13 (0.00)	0.10 (0.00)	1.00						
BTM	-0.10 (0.00)	-0.13 (0.00)	-0.08 (0.00)	1.00					
Patents	0.07 (0.00)	0.09 (0.00)	-0.01 (0.00)	-0.10 (0.00)	1.00				
R&D	0.05 (0.00)	0.11 (0.00)	-0.01 (0.05)	-0.21 (0.00)	0.32 (0.00)	1.00			
ROA	0.02 (0.00)	-0.07 (0.00)	0.06 (0.00)	0.04 (0.00)	-0.18 (0.00)	-0.53 (0.00)	1.00		
IE	0.02 (0.01)	0.03 (0.00)	-0.00 (0.41)	-0.01 (0.14)	0.04 (0.00)	-0.01 (0.01)	-0.00 (0.81)	1.00	
IO	-0.01 (0.28)	0.10 (0.00)	0.09 (0.00)	-0.08 (0.00)	0.26 (0.00)	0.00 (0.38)	0.01 (0.00)	0.20 (0.00)	1.00

Table 2: Innovative search focus and future operating performance

This table reports the average slopes (in %) and *t*-statistics (corrected for heteroscedasticity and serial correlation using the Newey-West correction with 12 lags) from annual Fama and MacBeth (1973) cross-sectional regressions of profitability in year *t*+1 on exploitation search focus and other control variables in year *t* from 1981 to 2006. Profitability is measured as either return on assets (*ROA*), defined as income before extraordinary items plus interest expenses scaled by lagged total assets, or Operating Cash Flow (*OCF*), calculated as income before extraordinary items plus depreciation and minus changes in working capital (defined as changes in current assets minus changes in current liabilities plus changes in short term debt and minus changes in cash) scaled by lagged total assets. The measure of a firm's relative focus on exploitative innovation in columns (1) and (2) is *internal search proximity* while in columns (3) and (4) we use our alternative measure *exploitative patent ratio* (see Section 3.2.2 for further details of the construction of these two measures). Δ*ROA* is the change in ROA between year *t* and year *t* – 1. *MTB* is market to book assets. *CapEx* is capital expenditure divided by lagged total assets. *R&D* is R&D expenditure divided by lagged total assets. *Patents* is the number of patents granted to the firm in year *t* divided by lagged total assets. All regressions include industry dummies based on the Fama and French (1997) 48 industries. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to have zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from the annual cross-sectional regressions.

	Internal search proximity		Exploitative patent ratio	
Profitability	ROA (Next year)	OCF (Next year)	ROA (Next year)	OCF (Next year)
Exploitation search focus	0.41	0.56	0.17	0.15
	(3.42)	(4.82)	(2.47)	(1.79)
MTB	-0.14	-0.18	-0.16	-0.19
	(-0.30)	(-0.52)	(-0.64)	(-0.52)
CapEx	0.42	0.67	0.42	0.68
	(0.93)	(5.11)	(0.93)	(5.36)
R&D	-0.76	-1.35	-0.75	-1.33
	(-4.06)	(-5.61)	(-4.05)	(-5.36)
Patents	-0.71	-0.85	-0.69	-0.81
	(-2.23)	(-7.41)	(-2.20)	(-7.31)
ROA	14.69		14.76	
	(7.68)		(7.68)	
ΔROA	-2.67		-2.68	
	(-8.17)		(-8.08)	
FCF		12.98		13.10
		(5.76)		(5.81)
ΔFCF		-4.03		-4.08
		(-12.66)		(-12.36)
Constant	1.84	2.56	1.78	2.40
	(0.89)	(0.93)	(0.87)	(0.88)
Average R^2	0.58	0.50	0.58	0.49

Table 3: Innovative search focus and earnings surprise

This table presents results from regressing earnings surprise in each of the four quarters in year t+1 on a firm's exploitation search focus in year t and other control variables from 1983 to 2006. Following So (2013), earnings surprise in a given quarter is defined as the realized difference between actual earnings per share (EPS) and the prevailing consensus EPS forecast in I/B/E/S scaled by total assets per share. The computation of *Exploitation search focus, BTM, R&D, Patents* and *CapEx* is defined in Table 1. *Momentum* for these purposes is the prior 6 month stock return leading up to earnings announcement (with one month gap between the holding period and the announcement month). *Accruals* are defined as total accruals in year t scaled by lagged total assets following Sloan, 1996. Return on equity (*ROE*) is calculated as income before extraordinary items in year t divided by lagged total equity. *Negative EPS* is an indicator for whether the consensus analyst EPS forecast for that quarter is negative (Fama and French, 2006). Following So (2013), we also include last quarter's realized earnings surprise for firm i (*Lagged ES*) and the change in earnings surprise between the prior two quarters (Δ*ES*) in all regression specifications. All regressions include industry dummies based on the Fama and French (1997) 48 industry classification scheme. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to have zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from the quarterly cross-sectional regressions. Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics are reported in parentheses.

	Internal search proximity		Exploitative patent ratio	
Dependent variable	EPS surprise	EPS surprise	EPS surprise	EPS surprise
Exploitation search focus	0.03	0.04	0.03	0.04
	(5.66)	(5.08)	(4.17)	(3.67)
Lagged ES	0.38	0.37	0.37	0.37
	(11.76)	(15.23)	(11.33)	(15.27)
ΔES	-0.15	-0.16	-0.14	-0.16
	(-5.18)	(-7.86)	(-4.78)	(-7.52)
ROE	0.12	0.11	0.12	0.12
	(3.03)	(2.30)	(3.01)	(2.26)
Negative EPS	-0.11	-0.07	-0.11	-0.07
	(-1.98)	(-1.07)	(-2.03)	(-1.04)
Accruals	-0.05	-0.04	-0.05	-0.04
	(-3.29)	(-3.51)	(-3.33)	(-3.42)
BTM		-0.08		-0.08
		(-3.41)		(-3.53)
Momentum		0.06		0.06
		(7.16)		(7.17)
R&D		0.01		0.01
		(0.44)		(0.41)
Patents		-0.04		-0.04
		(-4.26)		(-4.04)
CapEx		-0.03		-0.03
		(-1.88)		(-1.82)
Constant	-0.07	-0.25	-0.15	-0.34
	(-0.40)	(-3.26)	(-0.90)	(-4.66)
Average R^2	0.20	0.23	0.20	0.22

Table 4: Portfolio returns and risk factor models

At the end of June of year *t* from 1982 to 2007, we sort firms independently into three groups (low [L], middle [M] or high [H]) based on the 30th and 70th percentiles of either a firm's *internal search proximity* or *exploitative patent ratio* score in year *t-1* and two size groups (small [S] or big [B]) based on the NYSE median size breakpoint at the end of June of year *t*. We hold these portfolios over the next 12 months and compute value-weighted monthly returns for each portfolio. We then calculate monthly size-adjusted returns of the three relative innovation focus portfolios as (S/L+B/L)/2, (S/M+B/M)/2 and (S/H+B/H)/2 respectively. This table reports the monthly average size-adjusted excess returns to these portfolios (defined as the difference between size-adjusted portfolio returns and the one-month Treasury bill rate, expressed in percentage terms) as well as the intercepts (α, expressed in percentage terms) and risk factor loadings from regressing portfolio excess returns on factor returns. We measure exploitation search focus by *internal search proximity* and *exploitative patent ratio* (as defined in Section 3.2.2) in Panels A and B respectively. Heteroskedasticity-robust *t*-statistics are reported in parentheses. *MKT*, *SMB* and *HML* are the market, size and book-to-market ratio factors of Fama and French (1993) whilst *MOM* is the momentum factor developed by Carhart (1997). *EMI* is the innovative efficient-minus-inefficient factor in Hirshleifer et al., 2013) while *RMW* and *CMA* are the robust-minus-weak factor and conservative-minus-aggressive factors in Fama and French (2015). *LIQ* is the liquidity factor developed in Pastor and Stambaugh (2003).

Panel A: Portfolio sorts based on internal search proximity

Panel A.1 – Fama French three-factor model

Portfolio	Exret (%)	*α (%)*	*MKT*	*SMB*	*HML*	R^2
Low	0.58	-0.16	1.10	0.44	-0.08	0.89
t-stat	(1.79)	(-1.35)	(35.96)	(6.83)	(-1.20)	
Middle	0.76	-0.02	1.09	0.38	0.06	0.91
t-stat	(2.57)	(-0.21)	(46.13)	(8.89)	(1.44)	
High	0.86	0.22	1.02	0.34	-0.19	0.92
t-stat	(2.86)	(2.43)	(42.80)	(7.67)	(-4.60)	
High-Low	0.28	0.38	-0.08	-0.10	-0.11	0.17
t-stat	(2.81)	(3.58)	(-2.98)	(-1.53)	(-2.09)	

Panel A.2 – Carhart four-factor model

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*MOM*	R^2
Low	-0.03	1.05	0.47	-0.13	-0.26	0.92
t-stat	(-0.33)	(38.30)	(11.13)	(-2.70)	(-6.38)	
Middle	0.08	1.06	0.41	0.01	-0.21	0.94
t-stat	(1.21)	(47.91)	(14.43)	(0.46)	(-8.16)	
High	0.26	0.99	0.36	-0.23	-0.17	0.94
t-stat	(2.58)	(47.51)	(8.16)	(-6.50)	(-6.79)	
High-Low	0.29	-0.06	-0.11	-0.09	0.09	0.17
t-stat	(2.66)	(-2.45)	(-1.98)	(-1.80)	(2.33)	

Panel A.3 – Fama French five-factor model

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*RMW*	*CMA*
Low	-0.02	1.06	0.40	0.08	-0.19	-0.26
t-stat	(-0.15)	(34.88)	(6.84)	(1.08)	(-2.33)	(-2.10)
Middle	0.02	1.09	0.34	0.05	-0.10	0.06
t-stat	(0.14)	(44.81)	(7.55)	(0.82)	(-1.73)	(0.64)
High	0.26	1.03	0.27	-0.25	-0.17	0.17
t-stat	(2.82)	(44.71)	(6.15)	(-4.48)	(-3.17)	(1.96)
High-Low	0.28	-0.03	-0.13	-0.32	0.02	0.43
t-stat	(2.46)	(-1.29)	(-2.68)	(-5.58)	(0.21)	(4.70)

Panel A.4: Fama French three-factor model plus EMI factor

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*EMI*	R^2
Low	-0.12	1.10	0.42	-0.08	-0.20	0.89
t-stat	(-1.01)	(35.97)	(6.58)	(-1.30)	(-1.81)	
Middle	-0.03	1.09	0.39	0.06	0.09	0.92
t-stat	(-0.38)	(46.65)	(9.15)	(1.46)	(0.99)	
High	0.17	1.02	0.36	-0.18	0.24	0.92
t-stat	(1.93)	(43.93)	(8.60)	(-4.53)	(2.90)	
High-Low	0.30	-0.08	-0.06	-0.10	0.44	0.20
t-stat	(3.03)	(-3.27)	(-0.95)	(-2.20)	(5.88)	

Panel A.5: Fama French three-factor model plus Liquidity factor

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*LIQ*	R^2
Low	-0.17	1.10	0.44	-0.08	0.03	0.89
t-stat	(-1.46)	(36.54)	(6.75)	(-1.23)	(0.64)	
Middle	-0.02	1.09	0.38	0.06	0.01	0.92
t-stat	(-0.22)	(46.18)	(8.86)	(1.39)	(0.03)	
High	0.22	1.02	0.34	-0.19	-0.00	0.92
t-stat	(2.45)	(42.66)	(7.66)	(-4.34)	(-0.09)	
High-Low	0.40	-0.08	-0.10	-0.11	-0.03	0.17
t-stat	(3.69)	(-2.99)	(-1.52)	(-1.93)	(-0.89)	

Panel B: Portfolio sorts based on exploitative patent ratio

Panel B.1 – Fama French three-factor model

Portfolio	Exret (%)	*α (%)*	*MKT*	*SMB*	*HML*	R^2
Low	0.58	-0.13	1.10	0.40	-0.10	0.88
t-stat	(1.83)	(-1.15)	(37.54)	(6.38)	(-1.61)	
Middle	0.84	0.08	1.12	0.39	-0.05	0.92
t-stat	(2.69)	(0.90)	(38.37)	(8.51)	(-1.11)	
High	0.85	0.21	0.97	0.32	-0.08	0.92
t-stat	(3.10)	(2.54)	(47.94)	(9.62)	(-2.19)	
High-Low	0.27	0.34	-0.12	-0.08	0.02	0.15
t-stat	(2.63)	(3.39)	(-4.79)	(-1.39)	(0.42)	

Panel B.2 – Carhart four-factor model

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*MOM*	R^2
Low	-0.02	1.05	0.44	-0.17	-0.28	0.93
t-stat	(-0.60)	(39.25)	(11.28)	(-3.59)	(-6.78)	
Middle	0.11	1.09	0.42	-0.09	-0.19	0.94
t-stat	(1.13)	(44.67)	(10.90)	(-2.55)	(-7.78)	
High	0.19	0.94	0.34	-0.11	-0.15	0.93
t-stat	(1.99)	(42.80)	(10.67)	(-3.16)	(-6.07)	
High-Low	0.21	-0.10	-0.09	0.05	0.13	0.24
t-stat	(2.08)	(-4.37)	(-2.16)	(1.04)	(3.46)	

Panel B.3 – Fama French five-factor model

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*RMW*	*CMA*
Low	0.00	1.05	0.35	0.05	-0.20	-0.25
t-stat	(0.04)	(35.93)	(6.07)	(0.63)	(-2.49)	(-1.90)
Middle	0.14	1.11	0.34	-0.05	-0.14	0.04
t-stat	(1.38)	(38.40)	(6.93)	(-0.73)	(-2.31)	(0.36)
High	0.21	0.98	0.27	-0.16	-0.10	0.20
t-stat	(2.50)	(50.00)	(7.46)	(-4.00)	(-2.04)	(2.66)
High-Low	0.20	-0.07	-0.08	-0.21	0.09	0.45
t-stat	(1.96)	(-3.07)	(-1.82)	(-3.74)	(1.38)	(4.99)

Panel B.4: Fama French three-factor model plus EMI factor

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*EMI*	R^2
Low	-0.10	1.10	0.38	-0.11	-0.22	0.89
t-stat	(-0.78)	(37.37)	(6.22)	(-1.74)	(-1.93)	
Middle	0.03	1.12	0.42	-0.04	0.29	0.92
t-stat	(0.32)	(39.80)	(9.62)	(-0.97)	(3.46)	
High	0.18	0.97	0.33	-0.08	0.12	0.92
t-stat	(2.20)	(48.55)	(9.77)	(-2.11)	(1.75)	
High-Low	0.28	-0.13	-0.04	0.03	0.35	0.23
t-stat	(2.83)	(5.00)	(-0.83)	(0.58)	(4.48)	

Panel B.5: Fama French three-factor model plus Liquidity factor

Portfolio	*α (%)*	*MKT*	*SMB*	*HML*	*LIQ*	R^2
Low	-0.16	1.10	0.40	-0.11	0.05	0.89
t-stat	(-1.40)	(38.62)	(6.30)	(-1.72)	(1.14)	
Middle	0.09	1.12	0.39	-0.05	-0.02	0.92
t-stat	(0.98)	(38.14)	(8.54)	(-1.00)	(-0.43)	
High	0.22	0.97	0.32	-0.07	-0.03	0.92
t-stat	(2.68)	(47.94)	(9.68)	(-1.95)	(-1.22)	
High-Low	0.39	-0.12	-0.08	0.04	-0.09	0.17
t-stat	(3.89)	(-4.99)	(-1.38)	(0.70)	(-2.39)	

Table 5: Innovative search focus and future stock returns

This table reports the average slopes (in %) and their time series heteroscedasticity-robust t-statistics from Fama-MacBeth (1973) cross-sectional regressions of individual monthly stock returns from July of year t to June of year t + 1 on exploitation search focus (defined as internal search proximity and exploitative patent ratio in year **t**-1 for columns (1)-(2) and (3)-(4) respectively) and other control variables. Size, BTM, ROE, CapEx, R&D, Patents, NS, Inst. Own, Illiquidity, IV and SKEW are defined in Table 1. Momentum is the prior 6 month returns (with one month gap between the holding period and the current month). ST reversal is the previous month's stock return. All regressions include industry dummies based on the Fama and French (1997) 48 industry classification scheme. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation. Average R2 is the time-series average of the R2 from the monthly cross-sectional regressions. The stock return data are from July 1982 to June 2008.

	Internal search proximity		Exploitative patent ratio	
Dependent variable	Monthly stock return	Monthly stock return	Monthly stock return	Monthly stock return
Exploitation search focus	0.11	0.07	0.09	0.06
	(3.37)	(2.41)	(3.07)	(1.93)
Size	-0.08	-0.12	-0.06	-0.12
	(-0.69)	(-1.10)	(-0.48)	(-1.08)
BTM	0.29	0.29	0.30	0.28
	(3.70)	(3.87)	(3.85)	(3.71)
Momentum	0.25	0.19	0.26	0.19
	(2.78)	(2.42)	(2.81)	(2.47)
ST reversal	-0.81	-0.92	-0.80	-0.93
	(-8.99)	(-10.48)	(-8.97)	(-10.49)
R&D	0.09	0.10	0.10	0.11
	(0.71)	(0.96)	(0.72)	(1.04)
Patents	-0.04	-0.02	-0.04	-0.02
	(-1.36)	(-0.96)	(-1.15)	(-0.59)
CapEx	-0.16	-0.11	-0.16	-0.07
	(-2.52)	(-1.57)	(-2.60)	(-1.13)
ROE	0.23	0.16	0.23	0.21
	(3.62)	(2.72)	(3.65)	(3.42)
Illiquidity		0.17		0.17
		(1.59)		(1.58)
NS		-0.22		-0.21
		(-3.98)		(-3.71)
Inst. Own		0.16		0.17
		(4.02)		(4.08)
IV		-0.04		-0.06
		(-0.21)		(-0.33)
SKEW		-0.05		-0.16
		(-0.21)		(-4.01)
Constant	1.40	0.86	1.38	0.67
	(4.09)	(2.03)	(4.05)	(1.51)
Average R^2	0.07	0.15	0.07	0.15

3.8 FIGURES

Figure 1: Innovative search focus and market factor returns (1982-2008)

This figure plots the return on the hedge portfolio of high exploitation minus low exploitation focused firms (using *internal search proximity* and *exploitation patent ratio* respectively) and the market factor returns (*MKT*) from 1982 to 2008 (where we annualize the observed six month returns for 1982 and 2008).

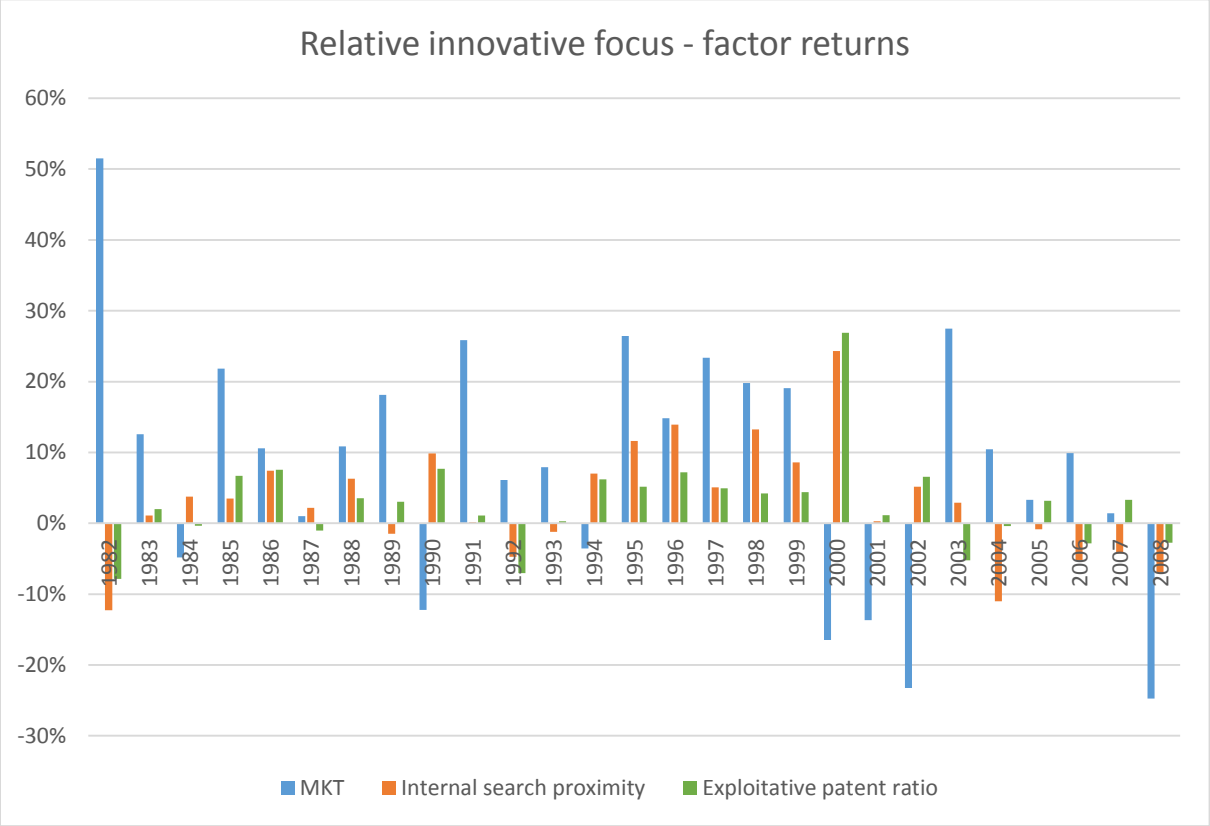
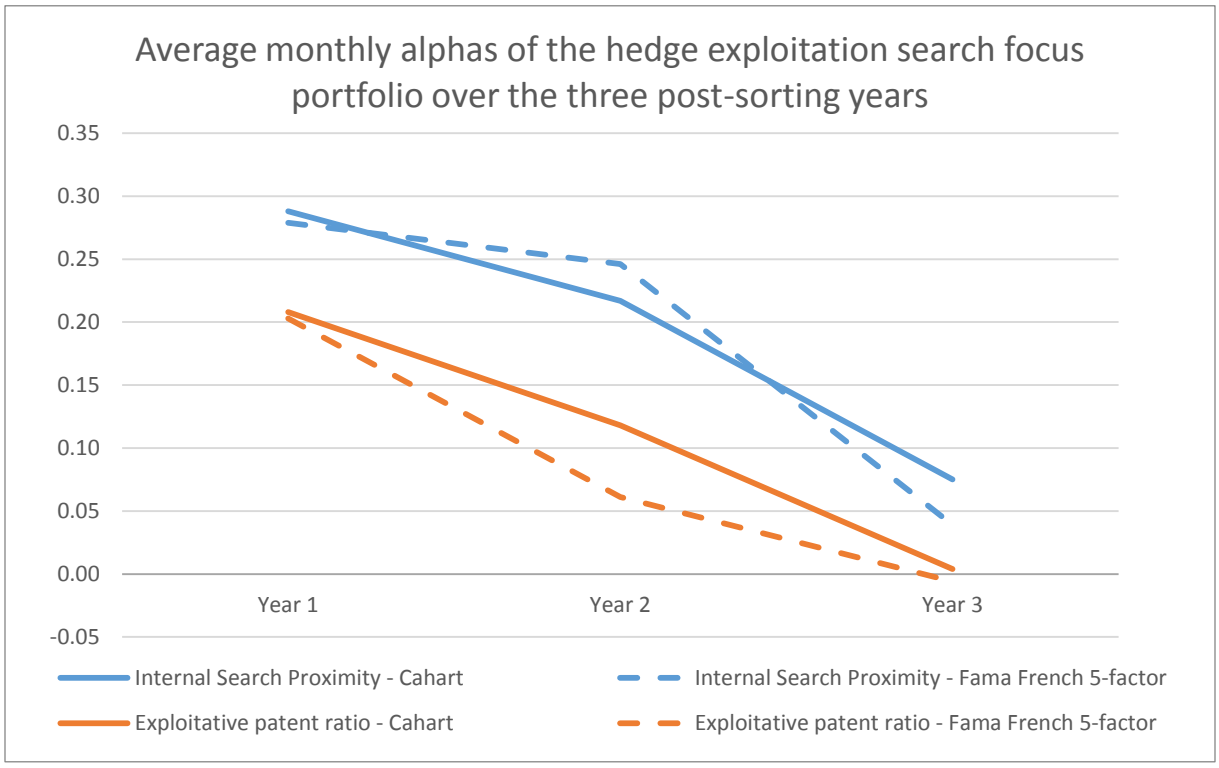


Figure 2: Monthly average alphas of High-minus-Low exploitation search focus hedge portfolio over the 3 years post portfolio formation

This figure plots the monthly average alphas for the High-minus-Low exploitation search focus hedge portfolio (formed using *internal search proximity* and *exploitation patent ratio* as described in Section 3.4.1) over the three post-sorting years. The portfolio alphas shown are calculated using either the Cahart four-factor model or the Fama & French five-factor model (see Section 3.4.1 for further details).



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Appendices

Appendix 1: Comparison of key contractual features in an entrepreneurial setting

Feature	IVC	CVC	Strategic alliance
Definition	• Investment firm focused purely on financial returns (IVC investor) acquires an ownership stake in an entrepreneurial firm that seeks capital to fund its R&D program	• Investment arm of an incumbent firm ("CVC investor") purchases an equity stake in a start-up firm to help fund R&D • CVC unit has strategic and financial objectives	• An established firm ("alliance investor") will contractually agree to make financial payments and share its technical, human & other resources with a start-up firm to aid development of the start-up's new project
Entrepreneur payoffs	• Receive equity interest in future firm cash flows • Payoff increases in their ownership stake (x) and firm exit valuation (V)	• Similar equity based payoff structure as IVC • However, exit options may be constrained by equity ownership of CVC investor firm (Benson & Ziedonis, 2010)	• Payoffs limited to receipt of milestone payments and royalties (based on the royalty rate, r, and product sales) • Typical royalty rates of 3-7% of future sales
Corporate financier payoffs	• Not applicable	• Receive equity interest in future firm cash flows • Payoff increases in their ownership stake (y) and firm exit valuation (V) • May seek to acquire full control of portfolio firm	• No payoff if no sales of new innovation are made • Conditional on project success, alliance investor receives most of cash inflows ((1 - r) × Sales)
Governance	• IVC investors receive multiple Board seats and have input into corporate-level decision-making • Founder/CEO controls R&D project operations	• Governance structure is similar to IVC although CVC investors often have restrictions placed on their voting powers (see Masulis & Nahata, 2009)	• Establish a joint steering committee to oversee R&D project operations (usually same number of members for each party)
Division of research responsibilities	• Exclusive responsibility of entrepreneurial firm	• Exclusive responsibility of entrepreneurial firm	• Primary responsibility on entrepreneurial firm, but alliance investor will give technical assistance
Division of product development responsibilities	• Exclusive responsibility of entrepreneurial firm	• Primary responsibility on entrepreneurial firm, but CVC investor may offer some technical assistance	• Primary responsibility on the alliance investor
Division of product commercialization responsibilities	• Exclusive responsibility of entrepreneurial firm	• Primary responsibility on the entrepreneurial firm	• Primary responsibility on the alliance investor

Sources: Kaplan & Stromberg (2004); Dushnitsky & Lavie (2010); Higgins (2007); Lerner & Mergers (1998); Chemmanur et al. (2014); Alvarez-Garrido & Dushnitsky (2016).

Appendix 2: Inverse probability weighted regression adjustment (IPWRA) methodology

For my main empirical analysis, I use the inverse probability weighted regression adjustment (IPWRA) method devised in Wooldridge (2007), Imbens (2004) and Sloczynski & Wooldridge (2014) to semi-parametrically estimate the average treatment effect (ATE) of different financing structures (s_i = IVC, CVC or Alliance) on start-up firm innovation (*Y*).

The first stage of the IPWRA method is to estimate the probability $p\ s, x_i$ that firm i with individual covariates x_i experiences treatment s (i.e. the "propensity score"). I estimate $p\ s, x_i$ via a multinomial logit model with the following explanatory variables (*X*) which are described in further detail in Section 1.4.1. and Appendix 3:

1) *Industry technological proximity*: patent-based measure of the expected benefit of access to a corporate investor's technical resources
2) *Firm patent originality*: patent-based measure of the risk of costly knowledge transfers to corporate investors
3) *Disease prevalence*: measure of the potential market size for the start-up's new drug and the potential benefit of corporate investors' commercialization infrastructure
4) *Pre number of firm patents*: number of patents held by start-up firm pre-investment
5) *Pre firm patent citations*: the number of patent citations to firm patents pre-investment
6) *Pre founders' NIH grants*: amount of research grants given to founders pre-investment
7) *Pre number of founder patents*: number of patents invented by founders pre-investment
8) *Pre founder patent citations*: the number of citations to patents developed by founders whilst in prior employment (i.e. before founding the focal entrepreneurial firm)

In addition, I include therapeutic category fixed effects (Danzon et al., 2005) as well as time fixed effects (Kerr & Nanda, 2015).

The second stage of the IPWRA method uses the propensity scores $p\ s, x_i$ to fit weighted regression models of the outcome for each treatment level. These estimated coefficients are then used to compute treatment-specific predicted outcomes for each entrepreneurial firm. Specifically, the following minimization equation is solved:

$$\mu(S) = \min_{\alpha_s, \beta_s} \sum_{i=1}^{N} \frac{\left(\mathbb{I}(s_i = S) \left(Y_i - \alpha_s - \beta_s (x_i - \bar{X}) \right) \right)^2}{p(s, x_i)} \tag{6}$$

Firm observations that have similar pre-investment covariates but enter into different financing structures (overlapping observations) are given relatively more weight in the estimation process.

The predicted outcomes for each subject are then averaged to estimate potential outcome means for firms that receive IVC funding ($E[Y_i(IVC)|X = x, s_i = IVC]$), firms that receive CVC financing ($E[Y_i(CVC)|X = x, s_i = CVC]$) and firms that enter into strategic alliances ($E[Y_i(Alliance)|X = x, s_i = Alliance]$). Using these terms, one can calculate the following average treatment effects (ATEs):

- ATE of CVC financing relative to IVC financing -
  $ATE\ CVC - IVC\ = E[Y_i(CVC)|X = x, s_i = CVC] - E[Y_i(IVC)|X = x, s_i = IVC]$
- ATE of strategic alliance funding relative to CVC funding -
  $ATE\ Alliance - CVC\ = E[Y_i(Alliance)|X = x, s_i = Alliance] - E[Y_i(CVC)|X = x, s_i = CVC]$
- ATE of strategic alliance funding relative to IVC funding -
  $ATE\ Alliance - IVC\ = E[Y_i(Alliance)|X = x, s_i = Alliance] - E[Y_i(IVC)|X = x, s_i = IVC]$

An important property of the IPWRA estimator is that it is a "doubly robust estimator" in that its estimates are consistent if *either* the selection model of treatment probabilities *or* the outcome model of conditional means is correctly specified (Wooldridge, 2015).

Causal inference using the IPWRA approach requires that three key conditions are met. First, there must be "unconfoundedness" or mean conditional independence such that treatment assignment (*T*) to different financing structures is independent of potential outcomes when conditioned on the inverse of the estimated propensity scores (as a function of the observable firm and founder pre-investment characteristics) and a firm's drug candidate reaching Phase 2 clinical trials. Section 4.3 describes the substantial evidence supporting my key identifying assumption that the Phase 2+ firms in my quasi-experimental framework have comparable intrinsic quality. Combined with explicit measures for each of the three key sources of selection as well as pre-investment measures of firm/founder quality and therapeutic category/time fixed effects, I argue that any remaining differences in innovation outcomes across firms can plausibly be attributed to the treatment effect of financial contracting structure.

Second, the "overlap" or common support condition requires that all start-up firms have a non-zero probability of receiving each treatment (i.e. $0 < \Pr\ T = IVC, CVC, Alliance|X\ < 1$). The overlap plots in Figure 3 display the distribution of predicted probabilities of firms receiving each financing structure treatment according to their propensity score. For example, the top left plot displays the estimated density of predicted probabilities for receiving IVC financing for each firm that actually received IVC, CVC or strategic alliance funding. These overlap plots indicate no individual propensity scores tend towards 0 or 1 and that all structures do not have most of their mass at opposite ends of the distribution. In particular, there are a substantial number of overlapping cases of IVC-, CVC- and alliance-backed firms to permit robust comparison.

Finally, Austin & Stuart (2015) argue that weighting using the estimated propensity score must balance covariates between treated and control firms in the weighted sample. The following table shows the standardized difference in the observed baseline covariates between IVC-, CVC- and alliance-backed firms in the unweighted and weighted samples for the sub-sample of Phase 2+ firms. Crucially, all standardized differences in the weighted Phase 2+ sample are well below 10%, the generally accepted threshold for determining if there is meaningful imbalance in covariates (Austin & Stuart, 2015). More formally, a pairwise Imai & Ratkovic (2014) test does not reject the null hypothesis that propensity weights balance observed covariates across different financing structures (p-value = 0.83). As a result, the IPWRA approach appears to be a valid estimator of the causal effect of firm financing structure on drug development firm innovation.

This table presents the standardized differences of various pre-investment firm characteristics across different financing structures for the 'raw' (unweighted) sample and the 'weighted' sample (using first stage inverse probability weights) of the 773 entrepreneurial firms reaching at least Phase 2 clinical trials. The standardized difference compares the difference in means in units of the pooled standard deviation (Austin & Stuart, 2015). The first two columns show the standardized difference in IVC and CVC-backed firm characteristics while the last two columns show the standardized differences in CVC-backed and alliance-backed firm characteristics.

	IVC - CVC		Alliance - CVC	
Standardized differences	Raw	Weighted	Raw	Weighted
Industry technological proximity	-0.08	-0.03	0.20	-0.03
Firm patent originality	0.07	-0.01	-0.26	-0.02
Disease prevalence	-0.18	-0.03	0.12	0.01
Pre number of firm patents	-0.07	-0.02	-0.06	0.02
Pre firm patent citations	0.07	0.01	-0.08	0.01
Pre founders' NIH grants	-0.06	-0.03	-0.02	-0.02
Pre number of founder patents	-0.04	-0.03	0.03	-0.01
Pre founder patent citations	-0.08	-0.02	-0.06	-0.00

Appendix 3: Variable definitions - Chapter 1

Variable	Description
Panel A: Innovation outcome measures	
Post number of firm patents	Number of eventually granted patents filed by the entrepreneurial firm in the five year period after the first IVC, CVC or alliance investment in year t (i.e. year t+1 to year t+5) (otherwise referred to as "post-investment" patents).
Post firm patent quality	The number of citations that a post-investment patent receives divided by the average number of citations received by all patents granted in the same year and technology class.
FDA Approval	Dummy variable equal to one if the biotechnology company obtains FDA approval to market a new drug in the United States and zero otherwise.
New chemical composition	A dummy variable equal to one if the U.S. pharmaceuticals regulator, the Federal Drugs Administration (FDA), classifies an approved drug as a "new molecular entity" and zero otherwise.
Potential for major therapeutic advance	A dummy variable equal to one if the FDA assigns "Priority Review" status to a new drug application (NDA), assigns a "fast track designation" to a new drug candidate or permits the opportunity for "accelerated approval"
Radical drug	A dummy variable equal to one if the drug is classified as both a new chemical composition and a major therapeutic advance.
Technology class	A technology class, which clusters patents based on similarity in the essence of their technological innovation, is defined by a classification scheme developed by the Cooperative Patent Classification (CPC) initiative, a joint project between the European Patent Office (EPO) and the United States Patent & Trademark Office (USPTO). My unit of analysis is the CPC 'main group' technology classes (there are over 7,000 main groups of which around 200 are most relevant for the biopharmaceutical industry).
Panel B: Control variables	
Industry technological proximity	Based on Jaffe (1989), the "closeness" in technological space of the start-up firm's pre-investment patents (where a "pre-investment" patent is defined as an eventually granted patent filed before or during the first investment year) and the combined pre-investment patents of all then active corporate investors (defined as corporations that had made at least one biotechnology CVC or strategic alliance investment by the relevant first investment year) using patent counts in different CPC main group technology classes k: $$Industry\ TP_{i,t} = \frac{\sum_{k=1}^{K} f_{E,k,t}, f_{C,k,t}}{\left(\sum_{k=1}^{K} f_{E,k,t}^2\right)^{\frac{1}{2}}\left(\sum_{k=1}^{K} f_{C,k,t}^2\right)^{\frac{1}{2}}}$$ Where $f_{i,k,t}$ = the fraction of patents obtained by firm i ($i = E$ (Enterpreneur) or $i = C$ (All potential corporate investors)) in year t that are in technology class k. Technological proximity is bounded to be between 0 and 1.
Firm technological proximity	Similar to industry technological proximity except that it measures the proximity of the entrepreneurial firm's pre-investment patents and the pre-investment patents of its *actually chosen* corporate investor.

Variable	Description
Scaled patent originality	Patent originality is calculated as the Herfindahl index of patents cited by the firm's pre-investment patents, which captures the dispersion of the patent citations across technology classes. Scaled patent originality is patent originality divided by the average originality of all patents granted in the same year and technology class.
Pre number of firm patents	The number of eventually granted patents filed by the entrepreneurial firm up to and including the first investment year (otherwise referred to as "pre-investment" patents).
Pre firm patent citations	Number of patent citations to pre-investment patents up to and including the first investment year divided by the number of firm pre-investment granted patents.
Pre founders' NIH grants	The total amount of all National Institute of Health (NIH) awarded grants (in millions) received by the founders of the entrepreneurial firm in the 10 years prior to first VC or alliance investment.
Pre number of founder patents	The number of eventually granted patents filed by the firm's founders up to and including the first investment year, *excluding* all patents owned or licensed to the start-up firm (thus included in *pre number of firm patents*)
Pre founder patent citations	Number of patent citations to pre-investment founder patents up to and including the first investment year divided by the number of founder pre-investment granted patents.
Panel C: Measures of potential mechanisms	
Entrepreneur-Financier cross cites	The total number of times that an entrepreneurial firm's post-investment patent cites a patent of its corporate investor.
Propensity for experimentation	The weighted average number of clinical trials that an entrepreneurial firm conducts in each phase of the drug development process. I assign a weight (w_1) = 1 for each Phase 1 clinical trial, a weight (w_2) = 2 for each Phase 2 clinical trial and a weight (w_3) = 3 for each Phase 3 clinical trial to reflect the greater scale and costs associated with later stage clinical trials. $$Propensity = \frac{\#\ Phase\ 1 \times w_1 + \#\ Phase\ 2 \times w_2 + \#\ Phase\ 3 \times w_3}{\#\ Distinct\ phases\ reached}$$ For example, if a firm reaches Phase 3 testing and conducts two Phase 1 trials, two Phase 2 trials and one Phase 3 trial, then the investor's propensity for experimentation is calculated as: $$Propensity = \frac{2 \times 1 + 2 \times 2 + 1 \times 3}{3} = 3.0$$

Appendix 4: Post-investment innovation outcomes by therapeutic categories

This table shows, by therapeutic category, the IPWRA potential outcome mean and ATE estimates for the sample of firms that reached at least Phase 2 trials. Columns (1), (2), (3) and (4) are confined to the sub-sample of Phase 2+ firms that are focused on developing therapies for *Cancer*, *Infectious* diseases, Cardiovascular & Hematology (*CardioHema*) and the Central Nervous System (*Nervous System*). Panel A, Panel B and Panel C contain the potential outcome means and ATEs across different financing structures for the probability of obtaining drug approval, the number of patents generated post-investment and the average scaled forward citations per post-investment patent respectively. All variables are defined in Appendix 3. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. GMM standard errors are reported in parentheses.

Panel A: FDA approval

Prob(FDA Approval)	(1)	(2)	(3)	(4)
Therapeutic category	Cancer	Infectious	CardioHema	Nervous System
Potential outcome means:				
IVC	0.14	0.28	0.14	0.35
CVC	0.19	0.29	0.21	0.30
Alliance	0.35	0.39	0.36	0.31
Average treatment effects:				
CVC − IVC	0.05	0.01	0.07	-0.05
	(0.06)	(0.07)	(0.09)	(0.09)
Alliance − IVC	0.21***	0.11*	0.22**	-0.04
	(0.08)	(0.06)	(0.10)	(0.10)
Alliance − CVC	0.16**	0.10*	0.15*	0.01
	(0.08)	(0.06)	(0.09)	(0.10)
Overall likelihood of FDA approval[1]	0.12	0.17	0.13	0.19
Likelihood of approval from Phase 2[2]	0.22	0.29	0.24	0.29
Minimum trial phase reached	Phase 2	Phase 2	Phase 2	Phase 2
Observations	185	139	93	124

[1] Defined as the overall probability of FDA approval for drugs entering the pre-clinical trial phase
[2] Defined as the conditional probability of FDA approval for drugs that undertake Phase 2 clinical trials

Panel B: Quantity of patents post-investment

Log(1+post number of firm patents)	(1)	(2)	(3)	(4)
Therapeutic category	Cancer	Infectious	CardioHema	Nervous System
Potential outcome means:				
IVC	1.45	1.38	1.03	1.34
CVC	1.56	1.50	1.47	1.34
Alliance	1.97	1.95	2.30	2.00
Average treatment effects:				
CVC − IVC	0.11	0.12	0.44*	0.00
	(0.17)	(0.15)	(0.23)	(0.19)
Alliance − IVC	0.52***	0.56***	1.27***	0.67***
	(0.19)	(0.21)	(0.26)	(0.23)
Alliance − CVC	0.41**	0.44**	0.83***	0.66***
	(0.20)	(0.19)	(0.20)	(0.22)
Minimum trial phase reached	Phase 2	Phase 2	Phase 2	Phase 2
Observations	185	139	93	124

Panel C: Patent quality post-investment

Post firm patent quality	(1)	(2)	(3)	(4)
Therapeutic category	Cancer	Infectious	CardioHema	Nervous System
Potential outcome means:				
IVC	1.47	1.65	0.99	1.09
CVC	1.04	0.86	0.99	0.79
Alliance	1.01	1.37	1.37	0.77
Average treatment effects:				
CVC − IVC	-0.43	-0.79***	0.00	-0.30
	(0.31)	(0.29)	(0.37)	(0.24)
Alliance − IVC	-0.46	-0.28	0.38	-0.32
	(0.32)	(0.30)	(0.30)	(0.26)
Alliance − CVC	-0.03	0.51*	0.38	-0.02
	(0.26)	(0.28)	(0.29)	(0.22)
Minimum trial phase reached	Phase 2	Phase 2	Phase 2	Phase 2
Observations	185	139	93	124

Appendix 5: Variable definitions - Chapter 2

Variable	Description
Panel A: Corporate policy and firm value outcome measures	
Number of Internal Patents	The total number of patents that are filed by the firm in a given year (and subsequently granted). Sources: *USPTO and Berkeley Fung Institute.*
Average Firm Patent Quality	Scaled internal citations is the number of citations a patent receives divided by the average number of citations received by all patents granted in the same year and technology class. Average firm patent quality is calculated as the mean of the scaled internal citation measures (i.e. a firm-year measure). *Sources: USPTO and Berkeley Fung Institute*.
Acquisition Count	Number of acquisitions completed in a given firm-year. *Source: SDC.*
Acquisition Ratio	The sum of the available prices paid for all acquisitions made during the year, divided by the firm's market capitalization. *Sources: SDC, CRSP*.
Number of Acquired Patents	The number of patents that a firm acquires from external entities each year. *Sources: USPTO; Berkeley Fung Institute; Plainsite*.
Leverage	Total debt divided by the book value of total assets. *Source: Compustat*.
TMT Size	The total number of executive officers at the firm. *Source: Company annual and proxy filings.*
TMT Turnover	Number of executive officers who depart the firm for non-health related reasons during the year. *Source: Company annual and proxy filings.*
ROA	Return on assets, measured as operating income after depreciation normalized by the book value of total assets. *Source: Compustat*
Tobin's Q	Book value of assets plus market value of equity minus book value of equity minus deferred taxes, divided by the book value of total assets *Source: Compustat*.
Panel B: Firm characteristic control variables	
Firm Age	The number of years since the firm was incorporated. *Source: Company annual and proxy filings.*
Firm Size	Book value of total assets. *Source: Compustat.*
Scaled Cash	Cash and marketable securities divided by the book value of assets. *Source: Compustat.*
Scaled R&D	R&D expenditures normalized by the book value of total assets. If the R&D expenditures variable is missing, I set the missing value of zero. *Source: Compustat.*
Scaled Capex	Capital expenditures normalized by the book value of total assets. *Source: Compustat.*
Panel C: CEO characteristic control variables	
CEO Duality	Dummy variable equal to one if the firm's CEO is also the Chairman of the Board of Directors, and zero otherwise. *Source: Company proxy filings.*
CEO Age	The age of the firm's CEO. *Sources: Company proxy filings; Factiva.*

Variable	Description
CEO Female	An indicator variable equal to one if the firm's CEO is a female, and zero otherwise. *Sources: Company proxy filings; Factiva.*
CEO Tenure	CEO tenure in years. *Sources: Company proxy filings; Factiva.*
CEO Ownership	Percentage of common shares owned by CEO. *Source: Firm proxy filings.*
CEO PhD	Indicator variable equal to one if the CEO received a PhD degree and zero otherwise. *Sources: Company proxy filings, Factiva, web searches.*
CEO MBA	Indicator variable equal to one if the CEO received an MBA degree and zero otherwise. *Sources: Company proxy filings, Factiva, web searches.*
CEO Technical Education	Following *Jung (2018)*, this is an indicator variable that equals one if the CEO has an undergraduate or graduate degree in Science, Technology, Engineering or Mathematics (STEM), and zero otherwise. *Sources: Company proxy filings, Factiva, web searches.*
CEO Great Depression	Following *Malmendier et al. (2011)*, this is an indicator variable equal to one if the firm's CEO was born between 1920 and 1929, and zero otherwise. *Sources: Company proxy filings; Factiva.*
CEO Military	Following *Malmendier et al. (2011)*, this is a dummy variable equal to one if the firm's CEO has served in any country's military, and zero otherwise. *Sources: Company proxy filings, Dun & Bradstreet, Factiva, web searches.*
CEO Financial Expert	Following *Custodio et al. (2014)*, this is an indicator variable equal to one if a CEO has past experience in either banking or investment firms (two-digit SIC codes 60-62), in a finance-related role (Accountant, CFO, Treasurer, or VP of Finance), or in a large auditing firm (current and former top-tier companies: Pricewaterhouse, Deloitte, Ernst & Young, KPMG, Arthur Andersen, Coopers, Peat Marwick, Touche Ross). *Sources: Company proxy filings, Factiva, web searches.*
Inventor CEO	Following *Islam & Zein (2018)*, this is an indicator variable equal to one if the CEO has at least one patent registered in their own name. *Sources: U.S. Patent Inventor Database, company filings, web searches.*
CEO Overconfidence	Following *Malmendier & Tate (2008)* and *Hirshleifer et al. (2012)*, I use a press based measure of CEO overconfidence. I search Factiva for all news articles using the available unique firm code and search keyword "CEO." I cumulate articles starting from the first year the CEO is in office or 1980, when I begin my Factiva article search. For each CEO and year, I record: the number of "Confident" terms, namely: (1) the number of articles that contain the words "confident", "confidence" or variants such as overconfidence or overconfident and (2) the number of articles containing the words "optimistic," "optimism" or variants such as overoptimistic and overoptimism versus the number of Cautious terms, namely: (1) the number of articles using "pessimistic", "pessimism" or variants such as over-pessimistic or not confident/optimistic and (2) the number of articles using "reliable", "steady", "practical", "conservative", "frugal", "cautious" or "gloomy". CEO overconfidence for each CEO i in year t is an indicator variable that equals one if the cumulative number of articles up until year $t-1$ using Overconfident terms exceeds the cumulative number of articles up until year $t-1$ using the Cautious terms, and zero otherwise.

Appendix 6.1: Innovative search focus and future operating performance (with IE and IO)

This table reports the average slopes (in %) and *t*-statistics (corrected for heteroscedasticity and serial correlation using the Newey-West correction with 12 lags) from annual Fama and MacBeth (1973) cross-sectional regressions of profitability in year *t*+1 on exploitation search focus and other control variables in year *t* from 1981 to 2006. Profitability is measured as either return on assets (*ROA*), defined as income before extraordinary items plus interest expenses scaled by lagged total assets, or Operating Cash Flow (*OCF*), calculated as income before extraordinary items plus depreciation and minus changes in working capital (defined as changes in current assets minus changes in current liabilities plus changes in short term debt and minus changes in cash) scaled by lagged total assets. The measure of a firm's relative focus on exploitative innovation in columns (1) and (2) is *internal search proximity* while in columns (3) and (4) we use our alternative measure *exploitative patent ratio* (see Section 3.2.2 for further details of the construction of these two measures). Δ*ROA* is the change in ROA between year *t* and year *t* – 1. *MTB* is market to book assets. *CapEx* is capital expenditure divided by lagged total assets. *R&D* is R&D expenditure divided by lagged total assets. *Patents* is the number of patents granted to the firm in year *t* divided by lagged total assets. Innovative efficiency (*IE*) is the patent citations-based measure developed in Hirshleifer, Hsu and Li (2013). Innovative originality (*IO*) represents the average patent citation diversity across all patents granted to the firm over the past five years following Hirshleifer et al. (2017). All regressions include industry dummies based on the Fama and French (1997) 48 industries. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to have zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from the annual cross-sectional regressions.

	Internal search proximity		Exploitative patent ratio	
Profitability	ROA (Next year)	OCF (Next year)	ROA (Next year)	OCF (Next year)
Exploitation search focus	0.57	0.64	0.21	0.19
	(3.62)	(4.71)	(2.91)	(1.70)
MTB	-0.09	0.12	-0.11	0.10
	(-0.30)	(0.36)	(-0.39)	(0.29)
CapEx	0.27	0.71	0.30	0.75
	(0.51)	(4.56)	(0.57)	(4.92)
R&D	-0.78	-1.51	-0.75	-1.49
	(-3.63)	(-5.75)	(-3.66)	(-5.50)
Patents	-0.73	-0.87	-0.72	-0.85
	(-1.87)	(-4.70)	(-1.90)	(-4.68)
IE	-0.13	-0.01	-0.08	0.03
	(-1.06)	(-0.22)	(-0.62)	(0.40)
IO	0.20	-0.28	0.10	-0.03
	(1.73)	(-1.35)	(1.12)	(-0.89)
ROA	15.24		15.32	
	(7.43)		(7.36)	
ΔROA	-2.98		-2.99	
	(-7.72)		(-7.51)	
FCF		13.17		13.29
		(5.64)		(5.69)
ΔFCF		-4.18		-4.23
		(-12.01)		(-11.62)
Constant	2.12	3.60	2.07	3.43
	(1.08)	(1.50)	(1.07)	(1.41)
Average R^2	0.57	0.49	0.57	0.50

Appendix 6.2: Innovative search focus and earnings surprise (with IE and IO)

This table presents results from regressing earnings surprise in each of the four quarters in year t+1 on a firm's exploitation search focus in year t and other control variables from 1983 to 2006. Following So (2013), earnings surprise in a given quarter is defined as the realized difference between actual earnings per share (EPS) and the prevailing consensus EPS forecast in I/B/E/S scaled by total assets per share. The computation of *Exploitation search focus, BTM, R&D, Patents, CapEx, IE and IO* is defined in Table 1. *Momentum* for these purposes is the prior 6 month stock return leading up to earnings announcement (with one month gap between the holding period and the announcement month). *Accruals* are defined as total accruals in year t scaled by lagged total assets following Sloan, 1996. Return on equity (*ROE*) is calculated as income before extraordinary items in year t divided by lagged total equity. *Negative EPS* is an indicator for whether the consensus analyst EPS forecast for that quarter is negative (Fama and French, 2006). Following So (2013), we also include last quarter's realized earnings surprise for firm i (*Lagged ES*) and the change in earnings surprise between the prior two quarters (Δ*ES*) in all regression specifications. All regressions include industry dummies based on the Fama and French (1997) 48 industry classification scheme. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to have zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from the quarterly cross-sectional regressions. Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics are reported in parentheses.

	Internal search proximity		Exploitative patent ratio	
Dependent variable	EPS surprise	EPS surprise	EPS surprise	EPS surprise
Exploitation search focus	0.03	0.05	0.03	0.03
	(5.66)	(3.97)	(4.17)	(3.43)
Lagged ES	0.38	0.36	0.37	0.37
	(11.76)	(12.47)	(11.33)	(12.49)
ΔES	-0.15	-0.14	-0.14	-0.14
	(-5.18)	(-5.39)	(-4.78)	(-5.57)
ROE	0.12	0.04	0.12	0.05
	(3.03)	(2.00)	(3.01)	(2.05)
Negative EPS	-0.11	-0.12	-0.11	-0.12
	(-1.98)	(-1.57)	(-2.03)	(-1.61)
Accruals	-0.05	-0.02	-0.05	-0.03
	(-3.29)	(-1.47)	(-3.33)	(-1.53)
BTM		-0.07		-0.07
		(-2.86)		(-3.12)
Momentum		0.07		0.08
		(4.35)		(4.22)
R&D		0.00		-0.00
		(0.12)		(-0.09)
Patents		-0.03		-0.03
		(-4.02)		(-3.70)
CapEx		-0.00		-0.00
		(-0.32)		(-0.23)
IE		-0.01		-0.01
		(-1.43)		(-1.11)
IO		-0.01		-0.00
		(-0.86)		(-0.13)
Constant	-0.07	-0.21	-0.15	-0.32
	(-0.40)	(-3.50)	(-0.90)	(-3.55)
Average R^2	0.20	0.25	0.20	0.25

Appendix 6.3: Innovative search focus and future stock returns (with IE and IO)

This table reports the average slopes (in %) and their time series heteroscedasticity-robust *t*-statistics from Fama-MacBeth (1973) cross-sectional regressions of individual monthly stock returns from July of year *t* to June of year *t* + 1 on exploitation search focus (defined as *internal search proximity* and *exploitative patent ratio* in year t-1 for columns (1)-(2) and (3)-(4) respectively) and other controls. *Size*, *BTM*, *ROE*, *IE*, *IO*, *CapEx*, *R&D*, *Patents*, *NS*, *Inst. Own*, *Illiquidity*, *IV* and *SKEW* are defined in Table 1. *Momentum* is the prior 6 month returns (with one month gap between the holding period and the current month). *ST reversal* is previous month's stock return. All regressions include industry dummies based on Fama and French (1997) 48 industry classifications. We winsorize all variables at 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation. Average R^2 is the time-series average of R^2 from the monthly cross-sectional regressions. The stock return data are from July 1982 to June 2008.

	Internal search proximity		Exploitative patent ratio	
Dependent variable	Mth stock return	Mth stock return	Mth stock return	Mth stock return
Exploitation search focus	0.11	0.09	0.09	0.06
	(3.37)	(2.21)	(3.07)	(1.69)
Size	-0.08	-0.15	-0.06	-0.13
	(-0.69)	(-1.40)	(-0.48)	(-1.21)
BTM	0.29	0.30	0.30	0.31
	(3.70)	(3.56)	(3.85)	(3.54)
Momentum	0.25	0.17	0.26	0.16
	(2.78)	(1.97)	(2.81)	(1.95)
ST reversal	-0.81	-0.93	-0.80	-0.93
	(-8.99)	(-9.95)	(-8.97)	(-9.86)
R&D	0.09	0.09	0.10	0.11
	(0.71)	(0.81)	(0.72)	(0.94)
Patents	-0.04	-0.05	-0.04	-0.04
	(-1.36)	(-1.53)	(-1.15)	(-1.28)
CapEx	-0.16	-0.16	-0.16	-0.13
	(-2.52)	(-1.85)	(-2.60)	(-1.56)
ROE	0.23	0.19	0.23	0.22
	(3.62)	(2.98)	(3.65)	(3.43)
Illiquidity		0.04		0.03
		(0.29)		(0.18)
NS		-0.26		-0.25
		(-3.20)		(-2.89)
Inst. Own		0.16		0.16
		(3.83)		(3.82)
IV		0.03		0.01
		(0.14)		(0.05)
SKEW		-0.05		-0.10
		(-0.96)		(-2.67)
IE		0.02		0.02
		(0.56)		(0.65)
IO		0.02		0.01
		(0.42)		(0.25)
Constant	1.40	0.81	1.38	0.65
	(4.09)	(1.64)	(4.05)	(1.25)
Average R^2	0.07	0.16	0.07	0.17