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Abstract

Angel funding is an important source of capital for startup ventures (J. Sohl 2019), providing a similar level of capital as institutional venture capital (OECD 2011). But angel funding is challenging to study due to the informal nature of the activity. A common paradigm for new venture funding argues that new ventures initially fund their activities with angel investment and then, as they show success, make progress to commercialization and de-risk core venture propositions, ventures transition to more professional institutional (venture capital) funding. A belief in this paradigm can strongly influence early venture creation activities, and assumptions about the later availability of capital from institutional venture capital underpin many startup business plans. However, the literature exploring this phenomenon is very sparse, and the question of the relationship of angel to venture funding transition has rarely been studied. By analyzing a large and robust dataset, this thesis advances the understanding of the actual behavior of investors and the impact this early behavior, and the funding choices involved, have on company outcomes. This thesis also explores a novel form of venture investing and places it into a broader context of new venture funding that may help explain some of the key observations discussed. These fundamentally empirical studies examine the nature/reality of important entrepreneurial phenomena of interactions between angel and venture funding in novel ways, pose questions, and identify a set results that point to a potential market failure. Attempts are made to understand these results and place them into the contexts of both research theory and a broader understanding of entrepreneurial behavior; there certainly remain a set of unanswered questions and potential fruitful directions for future research.

Keywords: Biomedical ventures, angel financing, venture capital, corporate venture capital

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Chapter I. Introduction

A. Overview of the Dissertation

A common paradigm for new venture funding argues that new ventures initially fund their activities with angel investment and then, as they show success and grow, transition to more professional institutional venture funding. Angel funding is an important source of capital for startup ventures (J. Sohl 2019), providing a similar level of capital as institutional venture capital (OECD 2011). But angel funding is challenging to study, due to the informal nature of the activity. A belief in this paradigm of "angel first, venture later" can strongly influence early venture creation activities, and assumptions about the later availability of capital from institutional venture capital underpin many business plans. However, the literature exploring this phenomenon is very sparse, and the question of the relationship of angel to venture funding transition has rarely been studied. By analyzing a large and robust entrepreneurial dataset, this thesis challenges this traditional paradigm, the very definition of what venture capital investors do, and advances our understanding of the actual behavior of investors and the impact this early behavior, and the funding choices involved, have on company outcomes. This thesis also examines a novel form of venture investing and places it into a broader context of new venture funding that may help explain some of the key observations discussed. A potential substitute for institutional VC – corporate venture capital - is also examined for its impact using a novel approach and dataset. These fundamentally empirical studies examine the nature/reality of important entrepreneurial phenomena in novel ways, pose questions about a significant market failure in venture investing. Although attempts are made to understand these results and place them into the contexts of both research theory and a broader understanding of entrepreneurial behavior, there certainly remain a set unanswered questions, and potential fruitful directions for future research.

This dissertation is organized into five chapters. This chapter (Chapter One) provides a summary of the entire PhD thesis, explaining the motivation and research methodology while highlighting key contributions. Chapters Two to Four form the core of the thesis. Chapter Two explores and challenges a commonly held belief that in entrepreneurial ventures, angel funding typically precedes venture funding. This chapter demonstrates, through analysis of a large, multinational dataset called Crunchbase, that this investment pattern is, in fact, quite rare by creating a novel statistic, the "angel to VC transition rate" or A2VC. Chapter Three dives into a novel approach observed in the biotech venture capital community – new venture formation by venture firms acting as company founders – which may help explain findings in chapter Two. Chapter Four explores the impact from a subset of venture funding – corporate venture capital (CVC) – that is sometimes viewed as a complement or alternative to institutional VC by applying the A2VC statistic and the Crunchbase dataset to ask if CVC's participation changes outcomes for startups and provides strategic return to the CVC parent. The final chapter, five, provides a summary of the contributions of this thesis and suggests directions for further research and exploration.

B. Empirical Motivations and Research Questions

The author is a full-time entrepreneur, and the original motivation for this thesis stems from several observations as the CEO of an angel-financed biotechnology firm, Siamab Therapeutics. Siamab developed novel cancer drugs and was financed by a large group of angel investors. After a period of 7 years as CEO, the author was successful at negotiating an exit through a sale to a large, public pharmaceutical company. However, throughout this entire period, the company was unsuccessful at raising institutional venture capital in spite of significant scientific success, multiple peer-reviewed papers published, numerous patents filed and granted, and multiple partnerships negotiated with large pharmaceutical companies. After several hundred meetings with institutional venture capital the author began to wonder: how often, in fact, do angel-funded biotech firms go on to raise venture funding (or fail to?)

A second empirical observation also helped motivate this thesis. The author raised capital from over 80 angel investors and had worked closely with several angel groups in the Boston area. In many cases, as startups were pitching angel investors, future funding was regularly discussed. Typically, startups articulated the expectation that future funding would naturally follow from institutional venture capital, assuming early success, positive data, milestones achieved, and risks reduced. Institutional venture funds were viewed as an independent and additional source of capital. Although these future funding assumptions were often a key component used to justify the near-term funding decision, they were never justified with data.

The third motivating observation arose when a partner at a leading Boston institutional venture capital firm that focused on biotechnology investments gave a talk to a group of biomedical engineering PhD students at MIT in 2017. This investor showed a slide that claimed, simply and directly, “We do not take pitches.” By this, the speaker meant that his firm did not behave in the expected manner for a VC firm – they did not solicit or evaluate external business plans (pitches) from outside entrepreneurs. Instead, they had developed an extensive capability in venture creation, acting as founder and entrepreneur for each of their portfolio companies.

These three observations are not reflected in the entrepreneurial finance literature. Angel investment is thinly studied, and only a single paper was identified that explored the transition from angel to venture funding in a small set of companies in a single Canadian city (Hellmann, Schure, and Vo 2019). Yet the policy implications stemming from these observations are profound.

The research questions that were formed to explore these phenomena include the following:

- How often do startups follow this traditional path of angel to venture funding?
- Can we better understand these results by exploring various industry groups and their rates of angel to venture financing?
- Does the emergent model of VC “venture creation” help explain angel to venture transition rates?
- How does the funding path of a startup associate with outcome measures?

C. Assumptions and Methodology

The core dataset used in this thesis originates with the Crunchbase dataset. Crunchbase is a commercial data company that collects and publishes rich data on venture funding (Dalle, Den Besten, and Menon 2017). It is notable – and novel – in having collected a large amount of angel investor data alongside venture capital investor. The angel investor has been consistently poorly represented in previous databases. The dataset developed by Crunchbase is of high quality but is certainly limited as Crunchbase relies on a both self-reported data by investors and startups, as well as a variety of publicly available data —including SEC filings and press releases to populate the dataset (Kemeny, Nathan, and Almeer 2017). Data are imperfect and incomplete, with gaps including full investor lists for investment rounds (i.e. some but not all angel investors may be listed) and lack of detail on how a syndicate in a round allocates the investment (i.e., who invests how much in a round.)

A central assumption implicit throughout this thesis is that in spite of these shortcomings, the Crunchbase dataset is broad and deep enough to provide informative source data for deep analysis and a novel lens to better understand angel-investor related phenomena. A second assumption is that the gaps in the Crunchbase data do not bias results in any particular direction but rather can be potentially filled by looking at a large enough sample size. We do know that over the past 20 years the quality of Crunchbase's data is richer with later companies so this particular bias much be taken into account.

Data analysis was performed through extensive use of the R statistical and programming language, and a large code base was developed to categorize investor and funding data and to develop funding history coding enabling the development and classification of the "A2VC" – angel to venture funding – statistic. Critically, investors were grouped into categories of angel, venture, and other investor types. This step ensured a careful sorting of investor types and further analysis of investment patterns based on investor type. Companies were categorized into several large groups – biotech/biopharma, other healthcare, energy, tech, and other, as has been done commonly across the literature.

An algorithm was developed to code each investment round for each company as an angel, venture, or mixed round and then the funding history for each round was used to develop a funding history pattern string encoding details on each round's funding. These patterns were subsequently analyzed and grouped into categories reflecting key subsets of funding patterns (i.e., companies that are born and remain in "angel land" – funded by angels through all rounds as companies – to companies that made the angel to VC transition.)

The Crunchbase dataset is very broad but relatively "shallow" – a very large number of firms coupled with basic demographic and deal information. This is useful when analyzing trends across large numbers of companies, geographically and over time. Chapter two relies heavily on the core Crunchbase dataset.

Chapter three is a focused study of venture funding of biotech ventures in Massachusetts comparing two time periods – 2007/2008 vs. 2017/2018. The key phenomenon examined in this chapter is venture founding/creation by venture capital firms. Crunchbase was used to identify the subset of companies to study. However, the information needed to determine if a venture was founded/created by a venture capital firm is not directly available in Crunchbase. Careful hand coding was required using a range of sources, including early press releases and company web sites, to determine the founding management team, as well as LinkedIn as a way to see if founding management was previously employed by the first venture investor(s). There is some subjectivity in this determination of "parental identification," but in cases where the CEO and other founding executives were previously entrepreneurs in residence at the

venture firm leading the A-round we have some confidence in this determination. Similarly, in some cases the first press release for a startup credits the venture firm as having "incubated" or founded the startup, and once again we can have high confidence in the role played by the VC in these cases.

Chapter four recodes investors from the Crunchbase dataset to distinguish more finely between corporate (CVC) and institutional (IVC) venture capital investors. Manual inspection and correction of this coding was performed to ensure an accurate grouping of IVC vs. CVC investors.

D. Contributions to the Literature

This dissertation contributes to several distinct literatures. The literature discussing angel investment is sparse given the challenges of researching the informal angel investment process. By studying in-depth angel investment behavior and performance and advancing knowledge about where angels invest, this study breaks new ground by exploring how follow-on funding post initial angel funding contributes to early angel-invested startups. There is also a small literature on angel investor returns, and this study also documents angel investment outcomes, exploring initial funding patterns and their association with differential positive outcome rates.

The second literature, on venture capital investing, to which this study contributes is much more deeply developed. However, the VC literature has not looked closely at precedent financing as a condition of venture investing. This dissertation challenges two fundamental assumptions – that VC is a common follow-on financing avenue for angel-funded firms and, centrally, the very definition of what VCs do – acting as "startup pickers" and investors. By documenting this novel VC approach of company creation – founding instead of funding – this dissertation both describes an evolution of VC behavior that may help explain some of the earlier findings (why angel-funded firms have trouble raising VC) and also highlights an important market failure in funding "scrappier" startups.

In one model, entrepreneurship can be viewed as experimentation, with VCs conducting a "portfolio of tests" across their portfolio (Kerr, Nanda, and Rhodes-Kropf 2014). In this model, staged financing creates real options, and enables investors to conduct these tranche by tranche, round by round "tests", killing unpromising ventures early before excessive capital is invested. By extension, we might expect that if the earliest financing is provided by angels – to conduct the first set of tests and derisking activities – that VC investors would appreciate these efforts and value the results; seeking investment with follow-on rounds in de-risked angel-financed companies. To the extent that this mechanism is less effective, angels -- as early investors -- may be creating novel "frictions" that counterbalance the reduced risk of successful early experiments. (Kerr and Nanda 2015)

This study also illuminates a previously undescribed example of the "paradox of entrepreneurship" – making (financing) choices requires testing/sampling various option. However, the very process of performing this testing and sampling by, in this case, raising a small angel round to run early-stage entrepreneurial tests, may preclude future financing options (VC) creating a path-dependency (Gans, Stern, and Wu 2019).

A final contribution, from chapter 4, extends the literature of corporate venturing and R&D externalization by looking for – but not finding - evidence of CVC venture impact on outcomes for the startup as well as R&D appropriation by the parent of the CVC. This study challenges an accepted paradigm of corporate venturing and raised several questions on agency and moral hazard at the CVC level.

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Chapter 2: The A2VC Paradigm Fallacy: Path Dependency Creates Two Distinct World of Startup Financing

Abstract. The “classic paradigm” of entrepreneurial finance, often taught in business and entrepreneurship classes, is that companies are launched by a founder with an idea, go on to raise angel financing, and ultimately, if successful, continue to grow their capital base by seeking venture financing. Ultimate success is achieved with an exit — either an M&A or IPO. This paper expands considerably on the work by Hellman et al. 2019 to examine venture funding paths and success rates using a large, international dataset: the Crunchbase database of venture financing. By coding the dataset to identify funding types at the round and company level, we can explore patterns of angel and venture financing. The dataset is analyzed to evaluate angel to VC (A2VC) investment transition patterns across industry, geography, time, funding amount, and investor experience level. Two key values are calculated across various industry, funding, and time-based groupings — a rate of A2VC and an entrepreneurial success rate, where success if defined as either an initial public offering (IPO) or an acquisition (M&A). It is clear that the “A2VC” rate is modest, particularly for biotech and clean tech companies, suggesting that the “classic paradigm” may not in fact be a significant path for most entrepreneurial firms. Importantly, biotech firms show a significantly lower A2VC rate than firms from other sectors (tech, energy, healthcare services), and this finding is true across all funding ranges, across time, and across geographies. The consistently lower A2VC rates of higher-risk and higher-capital-intensive biotech firms suggest a possible role for investor signaling and herd behavior as important drivers of these findings. These finding also suggest a possible gap in capital allocation with angel funded companies, and point to a possible market failure in biotech innovation.

A. Introduction

Angel Investment and Data

Angels are typically viewed as a key source of capital for early-stage companies; in the classic paradigm, successful angel-funded companies will "graduate" to institutional funding received from professional venture capital investors. Benjamin and Margolis (2000) state it well: "Angel investment runs the critical first leg of the relay race, passing the baton to VC only after a company has begun to find its stride." But how often does this transition from angel funding to VC funding ("A2VC transition") actually take place, and under what conditions?

The "Common Startup Investment Paradigm"

> (The) entrepreneur starts with friends and family to finance the early stage of the company up to where there is perhaps a prototype or Beta versions of the product. Angel investors most commonly fund the last stage of technical development and early market entry. Venture Capitalists will then come in with a 'Series A' investment to take the company through rapid growth and rapidly develop market share. (Adams 2013)

This common paradigm for startup company finance is a simple, linear model that is regularly articulated at business schools and other entrepreneurship education programs. This paradigm can be summarized as follows (Figure 1):

Figure 1: Classic Startup Paradigm	
Founding	Startup is founded by entrepreneur(s) "in a garage"
Seed funding	First funding is received by FFF – "friends, families, fools"
Angel funding	Early progress enables a larger angel round of financing
VC funding	With adequate progress/data/success, the founder(s) approach professional VCs for larger rounds
Additional VC funding	Multiple VC rounds may occur
Exit	IPO/exit/failure ends private financing efforts

Some companies may skip one or several steps in this paradigm, but it generally envisions a linear process of company development and corresponding capital raising activity/sources. Although not quantified in this "classic paradigm," one key implication is that successful early stage angel-funded companies that are operating in important areas, hitting their milestones, and achieving progress should naturally move on to raise VC funding, and this pattern should be true for a significant subset of these firms.

Angel investment is a large and important phenomenon in startup finance. Angel investors invest a magnitude of capital similar to that of venture capital investors. In the US in 2009, angels invested $17b and VCs invested $18b (OECD 2011); the Center for Venture Research estimated angel investment in 2018 to be close to $23B (J. Sohl 2019).

Angel investment is particularly challenging to study, however, due to several factors: angels typically operate in an informal and de-centralized manner; what data has been collected is typically the result of surveys, and self-reported data are subject to significant reporting bias; and as there are no Limited Partners to invest in angel funds, there is no market for data on angel performance. Therefore, no database vendors analogous to Venture Expert and others in the venture capital field are developing and selling such data in the angel community.

In the past decade, databases like Crunchbase have been developed that focus broadly on entrepreneurial startups and their funding. In many cases, they include data from angel investment rounds to the extent such data are available via press releases, self-reporting, and SEC filings. This paper uses the Crunchbase dataset, with additional coding and enhancement, to enable novel analysis of the angel investment field that was difficult to approach previously.

Recent trends in biotech funding appear to present a different paradigm. These include anecdotal observations of venture-funded biotechs starting their capital formation with large, institutional A rounds, having never raised an angel round. Consistent with this observation, a number of venture firms are now acting as founder/entrepreneurs and are playing more central roles in company formation (Booth 2019).

This paper seeks to explore the classic paradigm and to test how it matches reality by conducting a rigorous analysis of data from the Crunchbase database. Key questions include:

- How often do startups make the “A2VC transition”?
- Do industry and consequent capital intensity matter to the A2VC rate? How do A2VC rates vary between industries with higher capital requirements (i.e., biotech) vs. lower ones (tech/software)? We might expect venture firms to be the more frequent founding investors in capital-intensive industries, but when there is founding angel funding, we might equally expect to see a higher rate of angel to venture transition in these more capital-intensive fields.
- How does the A2VC transition rate vary across geographies, company age, total amount of capital raised, as well as over time?

Contributions developed in this paper include broadening the analysis initiated by Hellman et al. (2019) to a much large dataset that includes a longitudinal one covering top venture capital hubs (Boston, San Francisco), as well as diverse other geographies across the entire US. This paper also contributed by developing a novel statistic – the “A2VC” rate – which enables focus on and analysis of a complex, multi-party investment behavior. Finally, by diving deeply into the Crunchbase dataset and exploring not only funding patterns but venture performance by using exits as a proxy, this paper demonstrates how Crunchbase’s now leading dataset can be mined for novel insights into startup and investor behavior — in particular, offering a robust lens into previously opaque angel investor behavior for the first time.

B. Background and Literature Review

Angels operate in an idiosyncratic manner. Some of the key categories of angels include members of angel groups, exited entrepreneurs operating independently, and "super angels," who are much more active in investing larger amounts in many deals.

Figure 2: An Angel Typology				
	Investment size	# of deals/year	# deals/total	Decision process
Angel group members	10-100k	1-2	1-5	Group
High-net worth "solo" investors	50-500k or more	1-2	1-5	Individual
Super angels	25-500k or more	2-5	5-20	Individual
Crowdfunding	1k-25k	?	?	Group

Angel Investing Overview

Foundational descriptive research on the angel market includes annual studies by Sohl and the Center for Venture Research at the University of New Hampshire (J. E. Sohl 2017) and periodic reports published by the OECD (OECD 2011). These studies estimate the size of the angel market as $21.3b (J. E. Sohl 2017) and $17.7b in the US in 2009 and $18.3b in Europe in 2009 (OECD 2011). The OECD report describes angel groups and discusses different types of angels and processes used. Shane also reports a similar magnitude of investment by angels at $23b/year in 2001-2003 (Shane 2008). Importantly, these estimates for angel investment levels are similar in magnitude to annual venture investment levels. The challenge with these studies is that they aggregate large amounts of data, providing little granularity or understanding of actual patterns of investment. They also do not explore the temporal dynamics of evolving funding patterns in companies as they reach milestones and seek additional funding.

Angel Processes

The literature describes well the processes angels follow and the decision-making criteria used to screen entrepreneurs and candidate ventures to make investment decisions. As demonstrated by a study of an active and unusually well-documented angel group, Tech Coast Angels in Orange County, California (Sudek 2006), key criteria for the latter include trustworthiness, management team quality, enthusiasm of the founder, and exit potential. Learning theory has been applied to demonstrate the evolution in angel decision making and deal selection (Smith, Mason, and Harrison 2010). Angels often work together in formal and informal groups settings, and there are clear differences in the types of risks each is willing to invest in (Carpentier and Suret 2015). The relationships between angels and their CEOs is of course a critical element of the angel process, and early evidence of high levels of trust are correlated with angel investment performance (Bammens and Collewaert 2014). Not only do angels decide based on objective criteria (such as business plan, entrepreneur experience, market selection), they also respond to more emotional signals in their decision-making. For example, entrepreneurs who pitch angels successfully and receive funding demonstrate elevated levels of passion in their pitches, as perceived by the angels making the investment decisions (Mitteness, Sudek, and Cardon 2012). However, there is a dearth of evidence that links investment decision making and angel behavior to

portfolio company outcomes – both intermediate outcomes like follow-on funding as well as terminal outcomes such as exit/success/failure.

Angel groups appear to make investment decisions more slowly, but ultimately they can offer higher funding levels and show improved exit rates compared to individual investors (Sabarinathan 2017). However, the study referenced was limited in geography by focusing on Indian firms and their angels only. The set initially included angel-funded firms only, so it ignores the much larger set of early/seed venture-funded startups alongside those funded by angels at the outset.

Another area explored in the literature is how angel groups and their investments positively affect later outcomes of target companies, including future growth and survival rates (Kerr, Lerner, and Schoar 2011). The Kerr study is limited by its focus on a small set of companies from the portfolios of two angel groups (Tech Coast Angels and Common Angels), and the study does not explore future venture funding as a possible outcome.

Angel Returns

The literature discussing angel returns is particularly sparse, given the challenges in collecting robust and representative data. McDonald summarizes the return literature and notes how challenging it has been for researchers to develop and analyze datasets on angel returns, along with the particularly difficult issue of self-reporting bias that is endemic to angel investing (Michael B Mcdonald;Ramon P. DeGennaro 2016). One more heavily cited paper discussing returns is Wilbank's study of angel investment returns of angels in groups. However, this study uses self-reported data from a single exit per investor and therefore suffers from the potential of significant self-reporting bias (Wiltbank and Boeker 2007). Such challenges underpin the decision to treat documented IPO and M&A events as positive outcomes in this paper.

Venture Capital

There is a large literature exploring venture capital investing. Foundational papers discuss how venture investors make decisions (P. A. Gompers et al. 2020; Kaplan and Lerner 2010) – evaluation of teams, strategic considerations of the startup, deal screening and selection processes. Less "rational" mechanisms are also discussed including herding behavior and signaling (Connelly et al. 2011; Scharfstein and Stein 1990). The role of previous investment patterns – in particular angel investment as a precursor - as an element of VC decision-making builds on these studies.

The role of network effects and syndication between VCs is also an area of significant study (Fritsch and Schilder 2006; Sorenson and Stuart 2001). However, angel to VC networks and syndication are ripe for future study.

Kerr et al describe entrepreneurship as experimentation, explaining that VCs conduct a "portfolio of tests" across their portfolio (Kerr, Nanda, and Rhodes-Kropf 2014). This set of tests is a form of real options – offering the change to learn about opportunities in a staged manner, spending lower amounts of capital early on to gain enough information to make future financing and company "killing" decisions.

By extension, we might expect that if the earliest financing is provided by angels – to conduct the first set of tests and derisking activities – that VC investors would appreciate these efforts and value the results; seeking investment with follow-on rounds in de-risked angel-financed companies. To the extent

that this mechanism is less effective, angels -- as early investors -- may be creating novel "frictions" that counterbalance the reduced risk of successful early experiments. (Kerr and Nanda 2015)

This study also illuminates a previously undescribed example of the "paradox of entrepreneurship" – making (financing) choices requires testing/sampling various option. However, the very process of performing this testing and sampling by, in this case, raising a small angel round to run early-stage entrepreneurial tests, may preclude future financing options (VC) creating a path-dependency (Gans, Stern, and Wu 2019).

Angels and VCs

A number of researchers have modeled the theoretical relationships between angel and venture investors. Chemmanur develops a theoretical model exploring the relative value add of scarce venture investment vs. more available angel capital; his model assumes VCs add more value to ventures compared to angel investors (Chemmanur and Chen 2014). Hellman develops a model exploring "friend vs. foe" dynamics between angel and VC markets and argues that they are friends early in the life of a venture and foes later (Hellmann and Thiele 2014). Schwienbacher develops a model of optimization of choice between angels and VCs and analyzes the trade-offs resulting from various financing decisions (Schwienbacher 2009). All of these models, though elegantly constructed, suffer from the lack of real-world empirical data to inform and validate them; in addition, they do not allow for evolving patterns of angel and venture behavior over time.

Johnson and Sohl built a dataset of 799 firms that had undergone IPOs and examined the associations between early financing and post-IPO results. The authors argue that VCs and angels serve distinct subsets of entrepreneurial firms and therefore are not substitutes. This argument is consistent with some of the key findings of this paper – that angel-funded firms rarely become venture-funded and thus end up spending their entrepreneurial lives in different funding environments. However, the dataset used by the authors is small and focuses exclusively on IPO-exited firms and neglecting M&A outcomes, which are a significant contributor to entrepreneurial success (Johnson and Sohl 2012).

Goldfarb was able to obtain access to the detailed financing documents of 182 firms and compared series A financing terms among purely angel-funded, purely VC-funded, and mixed-funded firms. This analysis concludes that VC-funded firms have better exits than the other firms and postulates alignment and conflict of interest as possible explanations. The study does not look longitudinally at these firms however, so it is unable to examine funding paths over time and link these to outcomes (Goldfarb et al. 2013).

The paper closest to this analysis is Hellman 2019, which researches the relationship between angel and venture financing. Using a careful analysis of a set of 469 companies in British Columbia (primarily Vancouver) participating in an investor tax credit program that applied to both venture and angel investors, the authors explore the angel to VC transition. The companies studied in this region raised 2168 financing rounds from 9424 unique investors. The paper argues that angels and VCs effectively operate in parallel streams, and that companies in one stream rarely cross to the alternative stream. Specifically, they found that the probability of transitioning from an "Angel & no VC" round to a "No Angel & VC" round was 3.3%, and the probability of transitioning from "Angel & no VC" to "Angel & VC" one was 4.4%. The limitations of this study primary arise from geographic and temporal focus. The dynamics of a single region in Canada over a short period of time may not be generalizable across other regions where different industries flourish. In particular, with biotechnology being concentrated in

Boston and California (San Francisco and San Diego), a more global approach has the potential to offer an important perspective (Hellmann, Schure, and Vo 2019).

This paper contributes to the field by examining a much larger set of companies and investment rounds, specifically 99,732 investment rounds that funded 28,843 companies founded between 2000 and 2015 in the US. We subsequently compare this dataset to a similar dataset of ex-US companies. In addition, we follow the funding patterns of these companies for their entire lives, developing a novel coding that identifies types of funders in each round. Finally, we link these data to exit information to enable analysis of both round-to-round activities and founding through exit.

Historic Limitations of Research on Angel Investing

The academic literature on angels is sparse, as several key characteristics of angel investing make it difficult to study. Because many angels see their investing activity as a hobby, their own record-keeping varies widely, from rigorous to haphazard. Self-reported performance data suffer from significant self-reporting bias. Similarly, angel groups that aggregate pitches and evaluation activities often organize investors to invest individually and therefore struggle to track individual members' investment histories. Finally, there is no commercial market for angel investor data – unlike in the VC world, where LPs are willing to pay for high-quality aggregated return data to inform much larger investments into specific venture funds.

C. Data Source and Methodology

This study uses the Crunchbase dataset as the primarily source of data for analysis. The full dataset (644,893 companies) was downloaded on September 20, 2018. The Crunchbase data cover both angel and venture investments and are collected using a range of sources, including SEC filings, press releases, and self-reported data. The basic structure is company/round/investor whereby a company may raise multiple rounds, and each round may have multiple participating investors. In addition, IPOs and M&A transactions are tracked and coded to each company where relevant. The strength of the Crunchbase dataset is its breadth and size across multiple years and geographies.

There are significant limitations in the Crunchbase dataset as well. Each round has an estimated size, and multiple investors are listed for each one. However, the Crunchbase dataset does not provide more detailed information on the specific sizes of each investor's participation in a round. Furthermore, particularly in cases of multiple angel investor rounds, not all angels may be identified in the database. This may be due to limitations in the SEC filings, where only key investors may be limited, while press releases may also provide limited detail on the participating investors.

Other limitations in the Crunchbase dataset include an absence of industry and investment rounds in some records. Of the 644,893 companies in it, 227,779 are located in the US, and 193,600 have industry codes. Limiting the dataset further to US companies with an industry code, at least 1 funding round, and a founding date between 2000 and 2015 leaves 43,917 companies that are used in this analysis.

Groupings

For purposes of analysis, the following groupings were performed:

A. Grouping: Industry

Crunchbase identifies a wide set of industries, and these were grouped into four types: biotech, energy, health/MedTech and related services, and other (the majority of which are tech companies). These groupings were selected due to the potentially distinct characteristics of highly capital-intensive companies (biotech, energy) compared to other healthcare-related companies.

Table 2

Region	Count	Avg Funding	Std Funding	Avg Rounds	Std Rounds	Total Rounds
Ex-USA	417,114	$25,305,035	$262,677,098	0.24	0.74	101,554
USA	227,779	$25,124,919	$216,492,954	0.57	1.31	130,001
Total	**644,893**	**$25,208,756**	**$239,101,088**	**0.36**	**0.99**	**231,555**

Limited to: US companies, #funding rounds > 0, founding year 2000-2015.

Table 3: Breakdown by total funding raised

USA companies only, funding_rounds>0, 2000-2015							
Industry Type	**0**	**<$1m**	**$1.0m-4.9m**	**$5.0m-9.9m**	**$10m-49.9m**	**$50.0m+**	**Total**
bio	277	742	938	455	1,066	825	4,303
energy	184	191	169	81	165	165	955
health/med	695	800	691	262	430	191	3,069
other	3,153	3,197	2,069	710	1,076	469	10,674
tech	3,894	6,640	5,721	2,351	4,550	1,760	24,916
Total	8,203	11,570	9,588	3,859	7,287	3,410	43,917

Table 4: Summary stats for core segment (US, rounds>0, 2000-2015)

Industry Type	Count	Avg Funding	Std Funding	Avg Rounds	Std Rounds	Avg Company Age	Std Company Age	Rounds
bio	4,303	$32,904,690	$80,039,093	2.9	2.4	9.1	4.2	12,692
energy	955	$55,039,167	$201,416,073	2.4	2.7	8.7	3.9	2,252
health/med	3,069	$13,102,616	$53,834,535	2.1	1.9	7.9	3.9	6,435
other	10,674	$12,887,249	$120,693,771	1.8	1.5	7.3	3.8	19,057
tech	24,916	$17,797,211	$187,427,270	2.3	1.9	7.5	4.0	58,376
TOTAL	43,917	$18,565,864	$158,873,267	2.2	1.9	7.6	4.0	98,812

B. Grouping: Investors

The Crunchbase identifies 23 investor types. These were grouped into three categories: Angel, VC, and Other. The primary criteria to assign Category=Angel is based on the idea that Angels invest their own money and are not typically professionally employed to invest. Type=VC is based on the idea of a professional private equity investor group investing limited partner's capital. Type=Other includes government, accelerator, and university-associated funds.

Uncoded investors were subsequently assigned types as follows:

- Investors with dual roles as both "Investors" and "Company" were assigned "Corporate Venture Capital."
- Investors with names incorporating "Angel" were assigned "Angel."
- If the name of the investor has the words "Venture,"" Capital," "Partner," or "Fund," then the Type is assigned "Venture Capital."
- Investors with names incorporating "School" or "Foundation" were assigned Type = "University Program."

Although over 34k investors are not coded by type/category, 31k of these do not have any investments associated with them and can be safely ignored for this analysis.

Table 5: Investor Types and Counts (ALL)

Investor Type	N	Investor Category
angel	20,983	angel
investment_partner	12,115	angel
accelerator	2,028	angel
angel_group	1,199	angel
incubator	944	angel
family_investment_office	377	angel
co_working_space	183	angel
entrepreneurship_program	85	angel
startup_competition	22	angel
university_program	490	other
government_office	365	other
pension_funds	13	other
technology_transfer_office	2	other
Missing In Source Data	34,574	unknown
venture_capital	15,969	vc
corporate_venture_capital	11,747	vc
private_equity_firm	3,671	vc
micro_vc	1,756	vc
investment_bank	726	vc
hedge_fund	246	vc
fund_of_funds	169	vc
venture_debt	155	vc
secondary_purchaser	15	vc
syndicate	3	vc
other	1	
Total	107,838	-

Table 6: Investor Category Counts (ALL)

Investor Category	N
angel	37,936
unknown	34,574
vc	34,457
other	871
Total	107,838

The following chart illustrates the spread of investor experience (measured by number of rounds in which they have participated) and by category. Investors with 10 or more rounds are grouped together.

Table 7: No. of rounds of distribution across investor types (ALL)

Investor Category	0	1	2	3	4	5	6	7	8	9	10	Na	Total
angel	3	17,050	3,292	1,375	666	458	308	237	170	175	1,324	12,878	**37,936**
other	0	297	92	48	25	16	19	15	14	6	139	200	**871**
unknown	16	2,809	436	151	69	42	36	19	14	6	19	30,957	**34,574**
vc	11	12,382	3,816	2,024	1,164	859	613	492	463	345	4,284	8,004	**34,457**
Total	**30**	**32,538**	**7,636**	**3,598**	**1,924**	**1,375**	**976**	**763**	**661**	**532**	**5,766**	**52,039**	**107,838**

C. Grouping: Rounds

A total of 233,152 rounds are identified in the dataset, and 101,301 of these are associated with companies based in the US and founded between 2000 and 2015; 37 round types are identified by Crunchbase, coding each round. For the purposes of this analysis, each round was categorized as either Angel, VC, Public (i.e., post-IPO), and Other as follows:

Table 8: Round Type Groupings

Round Type	Round Category	Count
angel	angel	11,301
convertible_note	other	5,344
corporate_round	other	706
debt_financing	other	9,920
equity_crowdfunding	other	4,539
grant	other	11,106
initial_coin_offering	other	541
non_equity_assistance	other	3,265
post_ipo_debt	public	655
post_ipo_equity	public	3,257
post_ipo_secondary	public	21
pre_seed	angel	221
private_equity	vc	6,679
product_crowdfunding	other	760
secondary_market	public	433
seed	angel	66,780
series_a	vc	27,691
series_b	vc	15,290
series_c	vc	7,453
series_d	vc	3,219
series_e	vc	1,310
series_f	vc	473
series_g	vc	145
series_h	vc	47
series_i	vc	6
series_j	vc	1
series_unknown	vc	48,667
undisclosed	other	3,322
	Totals	233,152

This table shows the following descriptive statistics of this subset, including count, average total funding raised, standard deviation of total funding, and number of investors per round.

Table 9: Round Categories/Summary Statistics

Round Category	Count	Avg Funding	Std Funding	Avg Investor Ct	Std Investor Ct
angel	78,302	$828,781	$3,286,246	2.1	2.3
other	39,503	$13,457,426	$124,198,642	1.3	1.1
public	4,366	$123,567,727	$624,378,803	1.5	1.2
vc	110,981	$17,051,096	$115,811,963	2.5	2.1
Totals	233,152	$13,687,610	$134,416,028	2.2	2.1

D. Coding rounds by investor type

Although Crunchbase provides a code for type of round, we coded each round separately by examining all investors in each round. As described above, investors were previously grouped as either angel, venture, or other. Investor type was totaled for each round, providing a count of how many angel, venture, and other investors participated in each round.

We used the following round coding algorithm based on these investor type counts:

angel = 0 & vc = 0 → 'u' (unknown)
angel > 0 & vc = 0 → 'a' (angel)
angel = 0 & vc > 0 → 'v' (VC)
vc > 2 → 'v' (VC)

E. Coding companies → investor type pattern

After coding each round, an "investment trend pattern" (ITP) is calculated and assigned to each company, with a single letter representing each round type. For example, a company that has raised 3 angel rounds would be coded as "aaa"; a company with 4 venture rounds would be coded as "vvvv", and a company with 2 rounds – angel followed by VC – would be "av." The top 20 investment ITPs are identified in the following table, for all US companies founded between 2000 and 2015.

Table 10: Top 20 Investment Trend Patterns (ITPs)

Round Category Trend	N	Percent
u	11,184	25.5%
v	6,980	15.9%
a	3,965	9.0%
vv	2,653	6.0%
uu	2,232	5.1%
vvv	1,492	3.4%
vvvv	799	1.8%
uuu	788	1.8%
uv	775	1.8%
vu	733	1.7%
av	665	1.5%
aa	568	1.3%
au	448	1.0%
vvvvv	388	0.9%
uvv	352	0.8%
uuuu	348	0.8%
avv	313	0.7%
ua	306	0.7%
vvu	274	0.6%
va	271	0.6%
uuv	218	0.5%
vuv	213	0.5%

D. A2VC Rate – Definition, Calculation, Analysis

The investment trend pattern (ITP) tells us important longitudinal information about each company's funding history, telling the story of who funded each in sequence and enabling the identification of which companies began with angel funding and subsequently raise venture (institutional) funding. We call this specific pattern an "angel to VC transition."

We code each company as "A2VC" if it did not receive initial venture funding, if it did receive early angle funding, and if it subsequently had one or more venture rounds following initial funding. We can then calculate the ratio of A2VC to all companies in various company subsets.

I explore the data along the following dimensions – industry, region (US vs. ex-US) and "VC-hub" states like MA and CA vs others, total funding raised, and over time. This multidimensional, segmented analysis provides a holistic picture because it allows us to develop a series of internal controls on the data. So, for example, if the A2VC rate is lower for tech than biotech it could be hypothesized that this is a result of the differential capital requirements of these industries; by segmenting/controlling by total funding raised we can explore this question (and others like it) more precisely. I look at startup state (VC-hub states vs. other states) under the possible hypothesis that proximity to venture investors might influence the A2VC rate if companies physically closer to VC hubs have a chance to get to know venture investors more easily. I explore time-based effects to see if there is evidence for changes that could be associated with either secular economic trends, or perhaps the ongoing improvement of data quality in the Crunchbase dataset.

When limiting the universe to companies initially funded by angels only (US, 2000-2015, excluding unknown funding rounds), the A2VC rate is as follows across the key industry types:

Table 11: A2VC Rates in the US, 2000-2015

Industry Type	Count	Angel2VC Rate	P-value compared to Bio	Significance
Bio	2,640	5.0%		
Energy	567	5.6%	5.43E-01	
Health/med	1,758	6.5%	3.39E-02	*
Other	6,153	7.7%	7.83E-07	***
Tech	17,725	9.3%	5.14E-19	***
Totals	28,843	8.3%		

(Significance calculates a t-test between the bio rates and other industries.)
*=.05, **=.01, ***=.001)

We observe several key findings in this data set:

Finding 1: A2VC rates are low – the A2VC rate is 8.3% across the entire US/2000-2015 dataset. The vast majority of companies follow a singular funding path (angel or VC), and rarely do angel companies raise venture funding. These results are consistent with those of Heller (2017), suggesting that for most companies there is an angel path and a VC path, and the two rarely mix.

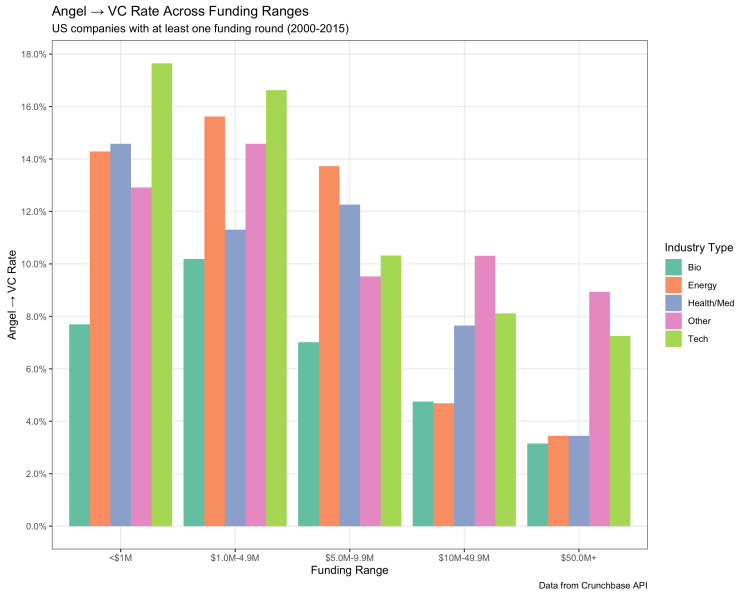
Finding 2: A2VC rates are significantly lower for biotech firms compared with all other industries, and in particular compared with "tech" companies (subcategories include hardware, software, IT, and internet firms). Tech firms have an overall A2VC rate double that of biotech firms.

Segmentation Analysis by Total Funding

One possible explanation for the low A2VC rate is that for more capital-intensive companies (i.e., biotech ones) there is a more significant separation between angel funding and venture funding. If capital intensity explained the gap between A2VC rates between biotech and tech firms, we would expect to see this effect reduced when comparing similar groups as measured by total funding. When stratifying by total funding raised, however, we see that the differences in A2VC rates between biotech and technology remain consistent across all total funding strata.

There are other differences between the biotech and tech industries that simple capital intensity. Product development timelines are significantly longer for biotech than for software and hardware development, and the risks are much more significant: alongside shared "market risk" much more pronounced technology, scientific, and regulatory risks occur in the biotech sector. These differences may help explain the gap in A2VC rates between these two industries.

Chart 1: A2VC rates – funding range and industry



Robustness Analysis: Segmentation Over Time

A second dimension to explore is that of time. Do these effects – low A2VC rates and significant differences between biotech and tech A2VC rates – hold true across the 15-year time period we are analyzing (2000-2015)? Showing the A2VC rates of biotech firms, tech firms, and all firms by founding year, Chart 2 demonstrates both consistently low rates and significant differences between the rates of biotech and high-tech firms.

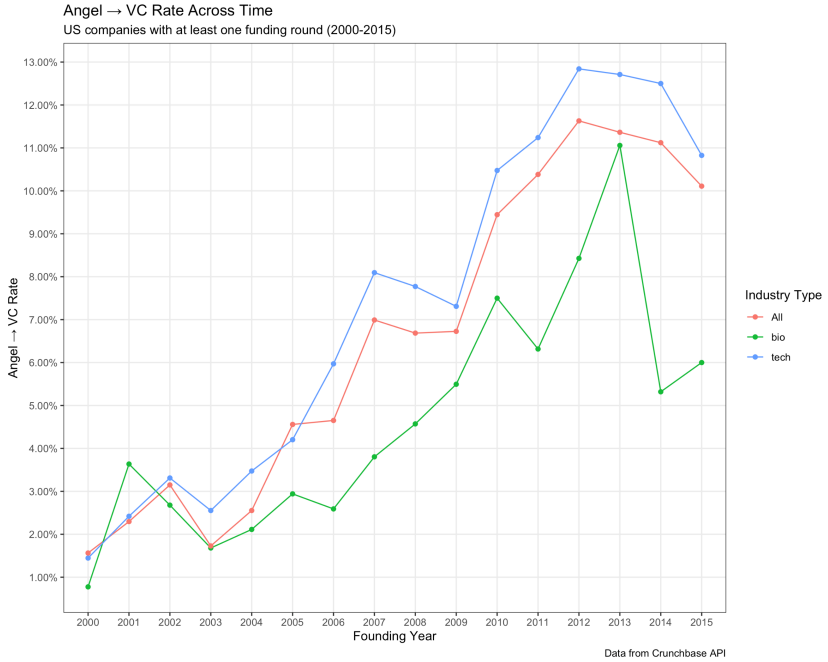
However, we do observe an unexpected trend – that the rate of A2VC does increase over time from 2000–2013. We do see a dip in the later years (2014, 2015), which may be explained by the fact that the transition to venture funding may take several years after initial founding. Hence, we can hypothesize that firms founded in 2014 and 2015 may make the VC transition in the next few years, and if this analysis was redone with additional years of data, we might see this effect mitigated (and repeated for the most recently founded companies in the dataset).

There are (at least) two possible explanations for this increased A2VC rate. This increase may in fact reflect a true phenomenon, perhaps due to better angel investment selection over time. Angel investment is relatively new: the proliferation of angel groups began in the '90s, alongside the first tech boom. Perhaps angels are getting better at investing, along with connecting with the venture community to the benefit of their portfolio companies. Also, as some of the recipients of the winnings from the tech boom go on to become investors, they can bring existing networks together with venture investors.

A second possible explanation is internal to the dataset used. Crunchbase has continually improved the quality of its database, and these improvements preferentially benefit more recently funded/founded companies. One specific example of this improvement is that Crunchbase has been developing relationships with institutional investors to provide data to enrich their dataset.

Unexpected finding 3: The A2VC rate increases over the time period observed in dataset. When we look at A2VC rates in biotech, tech, and all firms, we see a consistent trend of increase from 2000 to 2013.

Chart 2: A2VC Rates Over Time



Robustness by State – VC Hubs vs. Other States

Startups (and VC firms) are clustered into a few leading "high venture" states (MA, CA, NY, TX, and WA), and 60% of the companies in the dataset are located in these states. We can examine if these effects (low A2VC rates and differences between biotech and tech A2VC rates) vary between these states, and between the low-prevalence states grouped together.

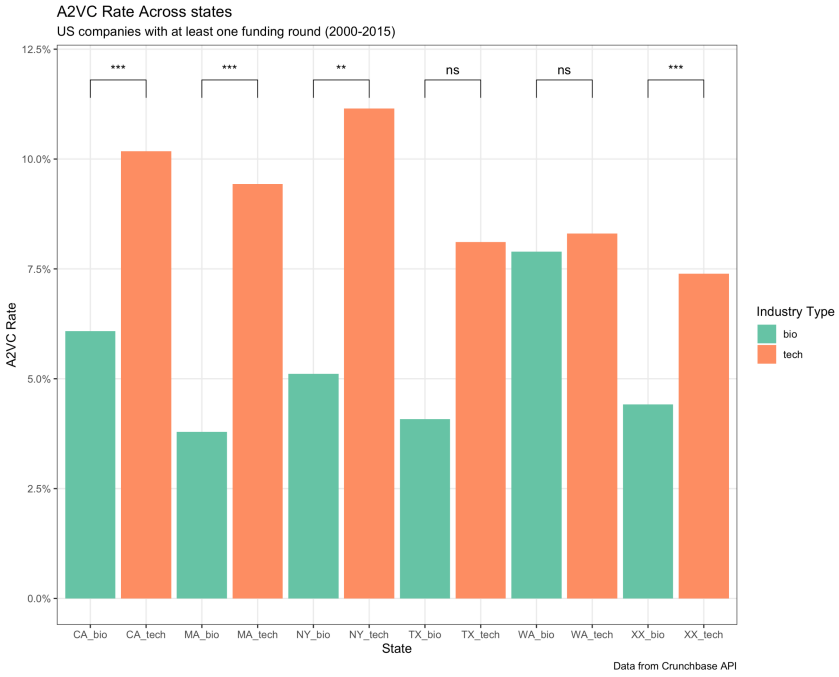
We see that the pattern of low A2VC rates and higher tech than biotech rates is consistent across all high-venture states, and across the group of low-venture states as well. We do observe an interesting difference between CA and MA firms, with biotech A2VC rates being significantly lower. Anecdotally, the

cultures of MA and CA venture firms are routinely compared, and these data may suggest a measurable example of these cultural differences.

We note that the A2VC rate trends upwards over most of the period studied, but in the last 3 years it trends dramatically down. This is not unsurprising, as the most recently founded firms in the dataset have existed only for a small number of years and have not had the time to raise 2nd and 3rd rounds, where an A2VC transition could occur. If this analysis were re-run with additional data from 2-3 years (i.e., in 2022), we would expect to see this short-term decline diminish in the 2013-2015 period (although it would be likely to exit in the last years of the period analyzed).

Unexpected finding 4: MA A2VC rates in biotech, but not in high tech, are significantly lower than A2VC rates in CA.

Chart 3: A2VC Rates in Biotech vs. Tech in VC Hub States and Other States

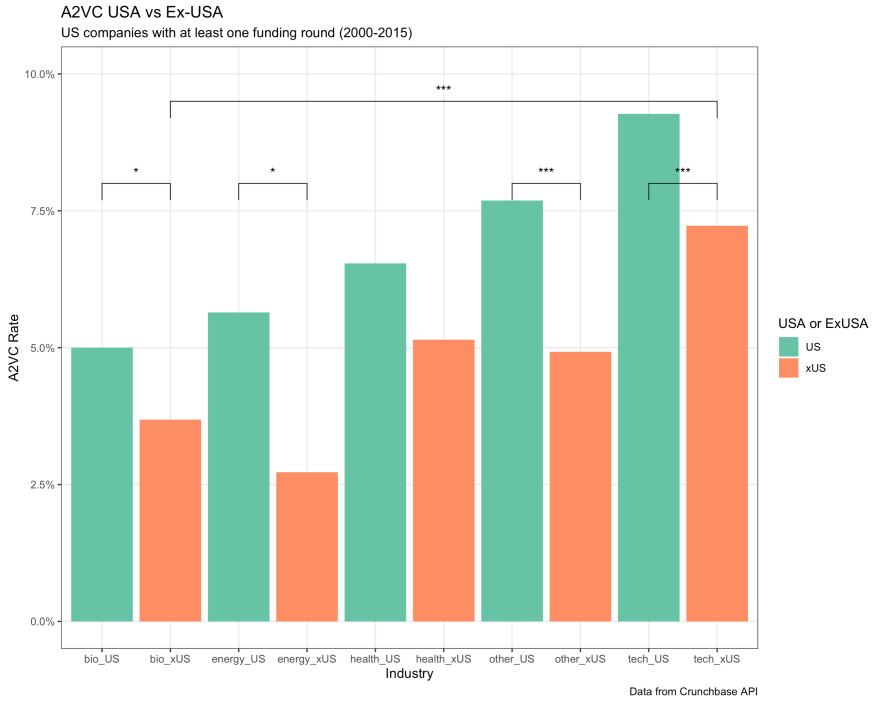


Note: XX=all states combined, excluding CA, MA, NY, TX, WA; NS= Not significant

International Analysis of Robustness — US vs. Other Countries

When we look outside the US, we see that the number of companies funded from 2000-2015 is similar in magnitude: 31,417 ex-US vs. 29,377 in the US. The investment funding patterns are similar between these two datasets, with the A2VC rate consistently lower across all industries. The dramatic difference between biotech and tech A3VC rates is maintained.

Chart 4: A2VC Rates Compared Between US and Ex-US Companies



E. Success Rates

Determining the success of an investment (for VCs/angels) or fundraising strategy (for startups) is challenging, given the limited data available at the company level in databases like Crunchbase. However, there are proxies for company and investor success that can be examined. Outcomes are encoded into the database for IPOs and mergers which can serve as markers for a positive outcome. IPO and M&A outcomes are commonly used in the literature as markers of entrepreneurial success (Croce, Guerini, and Ughetto 2018; Cumming and Dai 2010; Ivanov and Xie 2010).

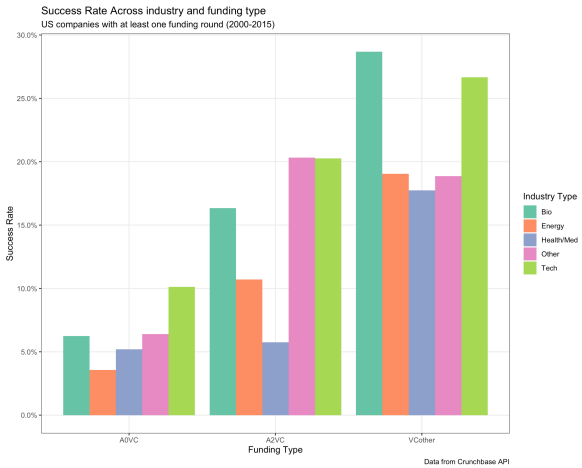
IPOs and M&A transactions are an imperfect proxy for venture success. With an IPO, investors are typically locked up for at least six months before they can sell shares and may hold shares for much longer to avoid depressing the price of a thinly traded company. M&A transactions could be high or low value ones, leading to positive or negative returns to investors. Given these potential limitations, such metrics do enable a preliminary examination of venture success in larger datasets.

In our US-focused dataset of funded ventures from 2000-2015, the overall exit rate was 21%. We observe in Table 12 that angel-funded companies that never transition to venture funding have the lowest exit rates; A2VC companies are next; and "pure venture" funded companies have the highest rates of exits in our dataset.

Table 12: Success (IPO or M&A) rates by industry and funding pattern

Industry Type	Angel, No VC	Angel then VC	VC but no Angel	Totals
Bio	5.9%	14.4%	29.4%	26.4%
Energy	3.7%	9.4%	20.0%	17.1%
Health/med	5.0%	7.0%	18.1%	14.4%
Other	5.9%	18.6%	19.2%	15.8%
Tech	9.7%	19.7%	27.0%	23.2%
Totals	8.0%	18.4%	25.0%	21.3%

Chart 5: Success Rates by Funding and Industry Categories



Note: A0VC = Angel but not VC fund; A2VC = Angel followed by VC funding, VC/Other = VC Funding from the first rounds

When we group the dataset into angel funded vs. VC funded (and allow A2VC firms to be counted in both sets), we can see dramatic differences in success rates between angel and VC funded companies across all industries in Table 14, as VC funded firms have double the success rates of angel firms. When we stratify firms by total funding received, we see that this observation holds true across all funding strata (Table 15).

Table 13: Success rates – comparing angel-funded vs. VC funded

Industry Type	Angel-funded Success Rate	VC-funded Success Rate	Totals
bio	8.8%	28.6%	26.4%
energy	5.3%	19.3%	17.1%
health/med	5.4%	17.2%	14.4%
other	8.9%	19.1%	15.8%
tech	13.1%	26.1%	23.2%
Total	11.2%	24.3%	21.3%

Table 14: Success rates: A vs. VC across funding ranges

Funding Range	Angel-funded Success Rate	VC-funded Success Rate	Significance
<$1M	6.5%	10.0%	***
$1.0M-4.9M	17.0%	20.5%	***
$5.0M-9.9M	13.4%	24.1%	***
$10M-49.9M	21.3%	31.1%	***
$50.0M+	27.3%	36.6%	**
Total	12.2%	25.3%	

Unexpected finding 5: Angel-funded firms have significantly lower success rates than venture-funded firms across all industries.

This trend of higher success rates for venture-financed companies compared to angel-financed ones holds true across both industry groups and funding levels. Since we observe that success rates of angel-funded firms are lower across all funding strata, we cannot simply relate successful outcomes to funding levels. Instead, we need to look at other possible explanations for this gap in success rates. Kerr et al. argue that angels provide additional value-add beyond capital (Kerr, Lerner, and Schoar 2011); perhaps the magnitude of this "value-add" is lower than the value-add provided by venture investors for the same capital provided. This could include industry expertise and networks/contacts, access to HR and hiring resources, access to partners, and expertise on partnerships and exit transactions. In addition, there could be a role for signaling taking place with venture firms' involvement that increases success rates: the fact that top-tier venture firms are invested in a company might increase the chance of a successful IPO or influence an acquiror to complete the exit transaction.

F. Discussion

By coding funding rounds with investor type, and companies with funding round trend codes that describe investor types for each round across multiple rounds, we enable a novel dimension of corporate finance and performance analysis that gains significant power when used in a large dataset such as Crunchbase. This coding and analytical process enables the exploration of important issues, including this paper's in-depth exploration of angel investment, which has historically been particularly challenging to study.

This study breaks new ground by carefully coding fundraising transactions and startup companies with investor type patterns, whereby each round is coded as an angel round, venture round, or unknown. Then each company is coded with a string of "round codes" to describe the series of investments it received; for example, AAA would indicate three angel rounds while AAV indicates two angel rounds and then a venture round. Finally, A2VC status is calculated (i.e., if the startup first received angel funding and subsequently received venture funding). Crunchbase also provides additional "demographic" and financial information about each company – total funding received, location, founding date, and exit information in the form of IPO and M&A dates as appropriate.

This coding and subsequent analysis of US-based firms founded between 2000 and 2015 demonstrated five distinct results:

> Finding 1: A2VC rates are low: 8.3% across the entire US/2000-2015 dataset.
>
> Finding 2: A2VC rates are significantly lower for biotech firms compared with all other industries, and in particular when compared with "tech" companies. This finding is robust across time and total funding strata.
>
> Finding 3: The A2VC rate increases over the time period observed in the dataset for both biotech and tech firms, as well as in the overall dataset.
>
> Finding 4: MA A2VC rates in biotech, but not high tech, are significantly lower than A2VC rates in CA.
>
> Finding 5: Angel-funded firms have significantly lower success rates than venture-funded firms.

We see both low A2VC rates across all industries, and biotech in particular. This observation suggests that the large majority of startups follow divergent paths, either as lower magnitude, angel-funded ventures living in "angel-land" with little chance to jump into "venture land" or as a venture-funded startup following a completely distinct funding path, with access to significantly more capital. In both paths, early funding sources are highly correlated with later funding, and very few companies are able to cross over to the other path.

This observation is potentially troubling for some angel-financed companies that envision larger funding requirements over time. A commonly used argument by new startups is that they will use initial angel funding to achieve early milestones and/or generate a preliminary dataset to demonstrate the successful first steps. In this paradigm, such early data would encourage venture investors to take a serious look at the startup and potentially participate in the next round of financing. Given that angel investors typically have thinner wallets and lower capabilities to continue to invest, this paradigm offers

a path for increased funding by more sophisticated investors who become involved after the angel. If this pattern is truly this rare (and becomes even more so in the biotech field, where capital requirements Increase dramatically over time), then angel-funded startups are running full speed into what may often be immovable walls.

Possible Explanations for Lower A2VC Rates for Biotech – A Signaling Theory Story?

One possible explanation for the lower A2VC rate for biotech compared to tech companies can start by observing some of the key differences between the two types of ventures today: biotech ventures are typically seen as higher risk, as more capital intensive, and as taking more time to develop successful products than high-tech ones. Today, software companies can rapidly develop prototypes, roll out beta tests, and use outsourced cloud-computing infrastructure to scale with little to no capital investment (Booth 2016)(Murphey n.d.).

Biotech's capital intensity remains particularly challenging. It can take over a decade to develop a drug from discovery through human trials, regulatory approval, and commercialization. Clinical trials are very expensive ($10-20m or more for a first human study [a "phase I" safety study]), and late-stage clinical trials are typically several times this cost as the number of patients and the trial's complexity rises through Phase II and Phase III studies. During this entire process, the firm is spending money but not earning it, so multiple financings are required to fund these ever-increasing costs.

One way some "platform" biotech companies secure funding to support these costs is by leveraging their broader technology platform to work on multiple drugs in parallel. If a deal can be struck with a large pharma group to work on drugs 2, 3, and 4, the funding from that deal may be able to be used to continue to progress with wholly owned drug 1 (and perhaps others). However, to convince a large pharma organization to agree to this deal (i.e., to fund a speculative and unproven platform to make novel drug discoveries) is challenging in itself, as there is typically little data to demonstrate success at this early stage.

Similarly, biotech IPOs often occur when only preliminary human results are available (Phase I safety data), and in some cases even before the clinical trial has been initiated. For drugs entering clinical trials, only a small percentage will make it through regulatory approval, and even fewer will have commercial success.

In the biotech field, we see that the decisions that VCs make to fund a B-round, a pharma group to make a platform deal with a startup biotech, and public market investors to engage with a new biotech IPO are similar – are all "data poor" decisions. Instead of being predicated on rich clinical data, these decisions must be based on other signals – including previous top-tier investors, prestigious founders, and ivy-league university affiliations. These signals of success can substitute for positive late-stage clinical data, regulatory approvals, and early sales results.

Perhaps we can begin to understand the challenges of the angel to venture transition through the lens of signaling theory. Signaling theory posits information asymmetry as the central feature that drives the value of signaling in economic transactions (Connelly et al. 2011). Interestingly, early stage biotech may be less of an example of information asymmetry than frank lack of information. No party involved in the development of an early stage drug has enough strong, useful knowledge to have high confidence in the potential success of the drug in the clinic. Historically, only 10% of drugs that initiate human clinical trials are approved ultimately by a regulatory agency (Hay 2014). Today, the only way to truly know if a drug

will be technically successful (i.e., safe and efficacious in humans) is to run costly and slow clinical experiments. Prediction and modeling remain unachieved "holy grails" in the biotech field.

In the absence of reliable information on a drug's future success, and taking into account the large capital requirements and long-time frames, sophisticated venture investors have begun to develop a novel approach to investing in the biotech field. These VCs are picking "big ideas" that are both amenable to making multiple bets (a wide pipeline), founding and seeding these companies themselves, making large initial investments, keeping syndicates small to control as much equity as possible, and partnering with pharma early and at high value to bring in large amounts of non-dilutive capital and additional prestige (signaling value).

Key to this emerging strategy is expertise in the key information around early stage biotech related to the potential for the early partnerability of a novel drug or platform and how "hot" the field is or will soon become. For example, gene editing — aka "CRISPR" — and cell therapies are current hot areas receiving significant attention, funding, and partnerships.

Another possible explanation for low A2VC rates may be the potentially negative signaling stemming from angel funding in the absence of venture (professional) funding. Perhaps venture investors see angel investment as a sign that the startup was not able to achieve top-tier funding – a classic example of adverse selection. In addition, as angel investors are typically less sophisticated and angel-funded cap tables may have many more participants than venture-funded firms, they may be perceived as a "hassle," with more potential investor risk acting as a negative incentive for investment.

Potential Explanations for the Phenomenon of Rising A2VC Rates Over the Period Examined and CA vs. MA Differences

This rise in the A2VC over the time period examined may plausibly be explained by the following factors. (1) increased capital flows into venture funds could subsequently drive more funding into previously angel-funded firms. With more dollars chasing startups, a broader set of startups could be receiving venture funds. (2) In addition, as angel investing matures and angels become more capable both in selection and management of investments, this could lead to better results in raising later-stage funding from institutional investors, causing a reduction in the adverse selection effect. (3) Finally, with the growth of the internet and generally better information flows available to all investors, information asymmetries may be declining, which could reduce the A2CV deficit as discussed above.

Another observable difference in A2VC rates was between the states of California and Massachusetts. The data suggest that the A2VC transition is significantly lower for Massachusetts-based biotech firms compared to those in California, but this is not the case for tech firms. Possible explanations include the following: (1) on the West Coast a closer set of ties exists between angel investors (many of whom were early Silicon Valley entrepreneurs) and venture firms compared to Massachusetts, where there is a smaller set of exited hi-tech angels. (2) Cultural differences exist in how venture firms behave, with Massachusetts-based VCs pursuing a "VC as founder" strategy more aggressively than in California (Booth 2017).

Potential Explanations for Lower Success Rates in Angel Firms, Even When Controlled for Funding Amounts

One possible explanation for lower success rates of angel-funded firms compared to those that are venture funded might be associated with the amount of future potentially available from the respective funding sources. Compared to institutional venture investors, angels have less capital to deploy - fewer "deep pockets"), which may create challenges for successful funding of future rounds or affect negotiating with potential partners from a position of funding strength or weakness.

In addition, signaling theory may also help explain differential success rates as well. Angel-funded firms may lack key success signals that venture investors may be providing; and second-order signals like pharma deals may amplify the signaling differential.

Finally, contrary to Kerr et al. 2011, the magnitude of meaningful venture assistance may be higher for venture investors compared to angel investors. In fact, the networks and expertise of venture investors may be most meaningful at the latter stages of entrepreneurial development, which precede successful exits.

G. Implications and Future Directions

Angel investment is a key funding source for startup companies, but in the vast majority of cases angel funding does not lead to venture funding. The transition from angel to venture funding is rare across all industry sectors, and it is particularly uncommon in the biotech industry. For the majority of firms, initial funding defines, and constrains, future funding. Angel-funded firms appear to have lower success rates than venture-funded firms across industries and funding strata.

The lower A2VC rates shown are robust across industry and are particularly pronounced with biotech firms; they are consistent across states, company size, total funding amounts, and countries.

Among the managerial/practical implications of these findings are the following:

- Startups need to carefully consider the later consequences of early financing decisions and the potential irreversibility of angel financing.

- For capital-intensive industries like biotech, a common view is that a startup can use early angel funding to develop a compelling dataset that will subsequently excite larger, venture investors to participate in later rounds. However, this idea (hope?) that data drives investments does not appear to the case in the large majority of cases. Alternative funding paths need to be planned for at the earliest stages of the venture.

- This study underlines an important gap in venture funding: if angel-financed firms in capital-intensive industries like biotech are rarely able to transition to venture financing, then they may be trapped on one side of the "valley of death," whereby they are unable to progress to value-creating (but expensive) clinical trials.

- There is a need for novel funding mechanisms to address this gap, with a focus on firms that are not funded by VCs. An example of such a mechanism is Cancer Research UK's Clinical Development Partnerships.

- Universities, startup accelerators, and business plan contests need to think carefully about the value they offer in getting startups off the ground and in helping them secure early, if modest, funding. If the path to additional, larger funding is highly constrained, then the lessons taught by these venture creators/supports may need to evolve.

Future Research Opportunities

Signaling theory is a potentially helpful framework to use in understanding the differential results of venture vs. angel investors. Future research questions to explore this domain further could include examining the signaling benefits of completing an A2VC transition that accrue to entrepreneurial companies. Also, another dimension of A2VC could be explored; i.e., when angel investors themselves undergo the A2VC transition to become venture investors. Some angel groups with strong leadership decide to raise venture funds, and successful angels may at times found institutional funds. The differential reputational status transition may offer an interesting look into the role of signaling in a dynamic and evolving system.

Network theory and syndication have been studied in the context of venture capital investments. Syndication patterns between leading angels and VCs would be a potentially fruitful area of exploration for extending this important field. It is possible to look at highly active vs. less active angels and use network analysis to explore who these various investor groups invest with and analyze outcomes (A2VC transitions; exit successes) along these dimensions.

The difference in A2VC rates observed across industries, in particular biotech and tech, appears to correlate with differences in capital intensity, technology risk, and product development timelines. This observation suggests that there may be fruitful avenues to explore in angel and venture funding across these different industries and firm characteristics.

Empirical questions that arise from this study may also be amenable to future study. In terms of additional exploration of the specific firms that do complete the A2VC transition, what is different about them? How are they able to do it? Similarly, elucidation of the set of venture firms that choose to invest in previously angel-funded companies might be interesting. Does this subset evidence different characteristics than venture investors who do not make these investments?

A deeper analysis of the specific angels and angel groups that are associated with the firms that successfully complete the A2VC transition might be telling. Is there in fact a concentration/" repeat transaction" effect observed? Or is the A2VC effect evenly distributed across the set of angels and angel groups? And if there is concentration, what can we learn about these specific angel investors that might explain it?

H. Conclusion

Using the Crunchbase dataset, we examined the commonly held assumption that angel financing precedes venture financing and found that this pattern of investment is, in fact, quite rare. This finding is important both at the practitioner and academic levels. Because the commonly held assumption of VC financing following angel financing motivates business plans and strategies of entrepreneurs, the fact that this is actually a rare event implies that entrepreneurs and early angel investors must plan for and seek alternative financing, rather than blithely assuming that VC funding will be available to startups demonstrating early success. This finding is also important to the literature because it may imply that venture investors are biased against angel funding, and are perhaps even creating a form of market failure. A fundamental question can be asked about the market efficiency of these private investment arenas, and if they prove to be less efficient then there is both untapped opportunity for investors and also important startups – and their technologies – that may be missing funding. This empirical study documents these results and identifies a series of future research questions that may prove fruitful for further study.

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Appendix: R Language Details and Packages Used

R version 3.6.1 (2019-07-05)
RStudio version 1.2.5019 (2019-10-24)
R package list:

```
#install. packages("openxlsx")
#install. packages ("flextable")
#install. packages("officer")
#install. packages("magrittr")
#install. packages("reshape2")
#install. packages("plyr")
#install. packages("lubridate")
#install. packages("stringr")
#install. packages("lazyeval")
#install. packages("scales")
#install. packages("countrycode")
#install. packages("tidyverse")
#install. packages("janitor")
#install. packages("survival")
#install. packages("timereg")
#install. packages("ggpubr")
#install. packages("aod")
#install. packages("stargazer")
#install. packages("plm")
#install. packages("DescTools")
#install. packages("arsenal")
```

Chapter 3: Is Biotech VC Dead?[1]

In recent years, the biotech world has seen a flood of scientific progress and commercial successes. It has been an exciting time for biotech investors, with total investment nearly doubling in the last 10 years alone (Pitchbook 2019). At the same time, a more subtle but possibly more important change has transformed biotechnology progress—changing the organization and financing of innovation, as well as the identities of teams commercializing science. This change is the shift from traditional venture capital (VC) financing, in which the investors take pitches from entrepreneurs and allocate capital across a range of independently conceived new ventures, to the "venture creation" model, where the venture capital firms themselves generate, incubate, and organize new companies.

This sea change, which we describe and document below, is (1) driven by rational responses to unique aspects of the biotech industry and (2) poses a new set of challenges for academic scientists and entrepreneurs. We argue that biotech and "tough tech" entrepreneurship – that is, entrepreneurship in domains that are particularly capital intensive, with long timelines to products and high technology risk – need a new taxonomy for distinct paths to commercialization to capture this new landscape properly. Further, we highlight implications for entrepreneurs, investors, universities, and governments, for whom conventional wisdom and policy has not yet caught up to the rapidly evolving landscape of biotech innovation.

A. Tale of Two Venture Worlds

The new world of biotech VC is a study in contrasts, providing lessons for diverse science-based ventures. On one end of the spectrum, promising commercial ideas—both broad and focused—sprout directly from academia. The more focused (e.g., a novel drug target) may emerge from a specific academic lab, which then struggles to get significant funding. Take AbBIO (Name changed to preserve requested anonymity), a company founded by a top researcher/clinician at the Brigham and Women's Hospital and Harvard Medical School. AbBIO is focused on a specific immune-associated target implicated in both auto-immune disease (where it is over-active) and cancer (where it suppresses immune function.) AbBIO received initial seed funding of $2.25M from a hospital innovation fund and 2nd tier ex-US VCs. The company raised a subsequent A round with a total of roughly $8M from the same investors, with no additional US investors participating. These investments provided the company with enough resourc[1]es to get through clinical manufacturing, but not enough to complete a first clinical trial (Interview with AbBio Founder 2019).

At the other end of the spectrum, and more surprising, are high-profile ventures founded in-house at venture capital firms. In these companies, the "founders" work within the VC firm (as partners, entrepreneurs-in-residence, or internal experts) to create companies—some with broad scope around big ideas and others more focused on a specific therapeutic area or disease pathway. Investing in *company creation infrastructure* (e.g., human capital or lab space), these venture firms typically dive deeply into the academic literature around an idea, convene experts to discuss early ideas, and even run

[1] This Chapter was co-authored with Dr. Josh Krieger. Behrens collected data, provided the statistical analyses and contributed to the writing; Krieger developed the theoretical framework, conducted the literature review and contributed to the writing.

first experiments to validate hypotheses, either themselves or with the help of academic and contract research organizations (CROs). In some cases, we have even seen these VCs identify and recruit scientific "founders" to provide expertise/credibility and to serve on the inaugural scientific advisory board. For example, Casma Therapeutics was founded out of Third Rock Ventures in Cambridge, MA in 2017/2018. The company has the broad and ambitious goal of using the cellular process of autophagy (cellular self-cleaning or recycling) to design new drugs. Four of the five founder executives (including the CEO, COO, and Chief Scientific Officer) were partners at Third Rock directly prior to working at Casma. In 2018, the company raised a $58.5M Series A round, led by Third Rock (Interview with Keith Dionne, CEO 2019; Linkedin 2019).

B. The Traditional VC Model Is Dead in Biotech: The Evidence

Informally and anecdotally, the message is clear to non-VC entrepreneurs: don't even bother trying to get premier VCs to fund development of your new drug idea. But sometimes trends are overstated and misinterpreted, so we went to the data. Focusing in on Massachusetts-based biotech companies - representing 25% of all biotech venture capital dollars (Carroll 2016) - with series A rounds greater than $5M, we coded which founding team members had previously worked at the relevant VC firms ("VC founded").

In 2007/2008, only 6 of 27 (22%) Series A rounds over $5m went to a VC founded company, while the numbers jump to 35 of 59 (59%) in the period 2017-2018, representing 71% of all biotech investment capital (see Figure 1). If we include biotechs founded by "star academics," serially successful entrepreneurs, and corporate spinouts, then we now include 50 of the 59 funded firms, leaving only 9 (15%) being founded in a more traditional entrepreneurial (or "scrappy") manner. This effect is even more dramatic one looks through the lens of capital invested: the capital allocated to this small set of "scrappies" is only 3% of the invested capital in the dataset.

Table 1

		# companies	% of total companies	Median A round	Total A round raised	% of capital invested
VC founded		35	59.3%	$41m	$ 1,463,662,183	71.4%
Not VC founded		24	41%	$24m	$ 586,740,942	28.6%
	Star academic	8	13.6%	$31m	$ 255,100,000	12.4%
	Serial entrepreneur	2	3.4%	$54m	$ 109,000,000	5.3%
	Spinout	5	8.4%	$31m	$ 155,540,942	7.6%
	Scrappy	9	15.3%	$8m	$ 67,100,000	3.3%
		59	**100.0%**		**$ 2,050,403,125**	**100.0%**

In addition to the change in the type of deals, average deal size rose for both the VC and non-VC founded companies during that period (see Figure 2, adjusted for inflation in 2018 dollars). In particular, the premier VC firms focused those investments almost entirely on internally founded companies (see Table 1).

Figure 1: VC-Founded Biotechs: 2007/08 vs. 2017/18

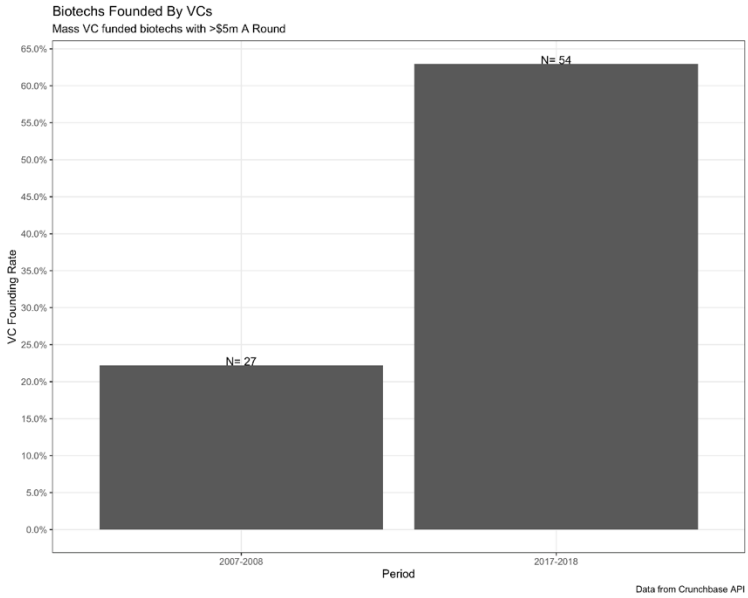


Figure 2: VC Founded Biotechs – Size of A-Rounds

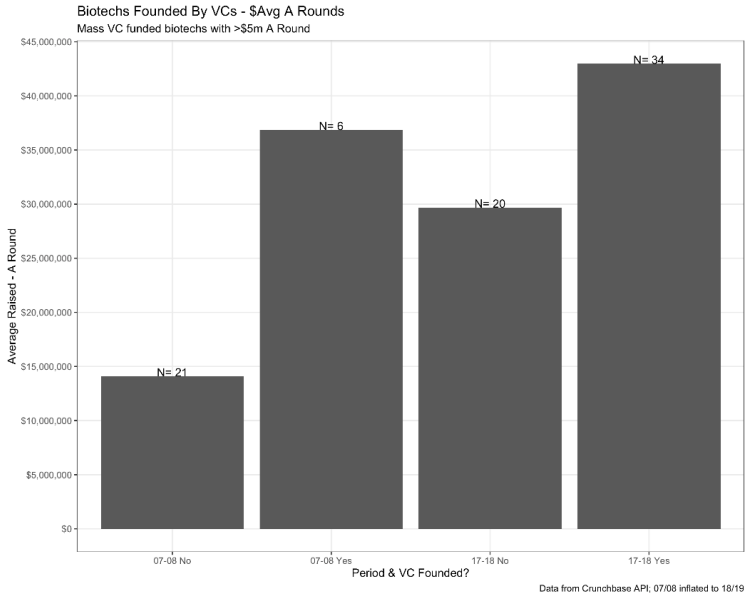


Table 2: Recent Deals by Large Boston-Based VCs

VC Firm	# deals 2017-18	# founded
Third Rock Ventures	10	9
Atlas	11	10
Flagship Pioneering	15	13
Polaris	9	6

C. A New Taxonomy

Given the relatively small number of non-VC founded firms, we were able to examine each closely and investigate their origin stories. If they were not coming out of VC venture creation machines, then where did they come from? Roughly half of the non-VC founded A rounds had at least one serial biotech entrepreneur founder or star scientist, while the remainder were split between corporate spinoffs and just a handful (9) that were neither star founders nor spinoffs. Rather than lumping these very different types of ventures together, we defined a new set of categories based on what we saw in the data.

BIOTECH FOUNDER TAXONOMY	
VC Founded	At least one senior exec from the founding VC. Typically, larger seed and A rounds, broader scope ventures, and smaller syndicates (often only the lead investor in the A round).
Corporate Spinoffs	Key intellectual property and leadership from incumbent corporate entity. Often receiving seed investment from corporate parent (or corporate venture arm).
Star Scientist Entrepreneurs	Well-known academic entrepreneur with a successful track record (e.g., Bob Langer, George Church, Greg Verdine), or serial biotech entrepreneurs (e.g., Eric Anderson, former founder of Adimab and Compass, Robert Mulroy, former CEO of Merrimack).
Scrappy Biotech Entrepreneurs	First-time founders (often out of academic labs) receiving early funding through non-dilutive grants (i.e., SBIR or foundations), angel funding, and second tier or foreign venture capital.

D. How We Got Here

In a world of perfect information and fully functioning capital markets, the financing of innovation should be optimized to meet market opportunities, resource demands, and risk profiles of any given technology area. However, in reality we see that financial systems shift over time—developing new modes of deploying capital as they experiment and learn, as well as in response to market factors. While we are not the first to identify the fact that biotech VC has shifted to the venture creation approach (Booth 2019), we break down the drivers of this shift into categories below, then discuss the implications for other "tough tech" industries.

High Technical Risk, Long Timelines, and Capital Intensity

Most biotech projects are highly uncertain, with expensive capital requirements (sometimes >$50M) and long timelines. Clever experiments and access to good partners and equipment might speed the process modestly, but quick-and-dirty prototypes ("minimum viable product" in the parlance of the Lean Startup movement) tell you little in the world of complex biology. ("It is much easier to cure cancer in mice than people.") Novel therapeutics require time and effort in the lab before one can even consider putting humans at risk—and we still don't know enough about biology to have confidence that

preclinical models can predict human response accurately. Furthermore, regulatory structures require many years of clinical trials before ventures can recover any revenue from their innovations.

The result: drugs may take many years (and hundreds of millions of dollars) before they fail. Take Stromedix, founded in 2007 by experienced scientist-entrepreneurs with the help of Biogen and Atlas Ventures. After $28M of venture capital, a $75M acquisition by Biogen, and 12 years of development, the drug recently failed in a Phase IIb clinical trial (Idrus 2019) in its goal of treating idiopathic pulmonary fibrosis. Biotech is hard and not for the faint of heart.

What do these high risks, long timelines, and large investment requirements mean for financing biotech? These characteristics rule out a "spray and pray strategy" such as seen in cloud-based IT/software businesses, since that would spread capital too thin and not allow enough time for ventures to reach key milestones (Ewens, Nanda, and Rhodes-Kropf 2018). While the timing of biotech milestones have not changed much, the pace of software and IT experimentation has sped up in recent years, as cloud computing has allowed for rapid prototyping, enabled faster and cheaper testing, and led to a greater number of smaller seed investments (Bruce Booth 2012). This divergence in investment needs makes it harder for biotech investments to coexist with other types of investments within a diversified VC portfolio. This shift is reflected in the increasing specialization of venture creation funds.

	Low capital required	High capital required
Short time to revenue	e.g., Software/apps "spray & pray" strategy	e.g., Movies, manufacturing facilities Concentrated investments + experience
Long time to revenue	e.g., Lifestyle businesses, small-scale agriculture, real estate speculation	Biotech (other tough tech?) Venture creation by VCs, smaller syndicates, "patient"

E. Learning and VC Math

It is easy to forget that venture capital investing is a relatively recent phenomenon, with the first funds starting just a half century ago. Nascent industries require trial-and-error before settling into industry norms and dominant operational logics. If anything, one might expect venture capital to have a long learning cycle, because it is a relatively small sub-sector of investing with long investment horizons. With funds in the 8- to 12-year time frame, fund managers and investors only get to update their views on "what works" maybe once a decade.

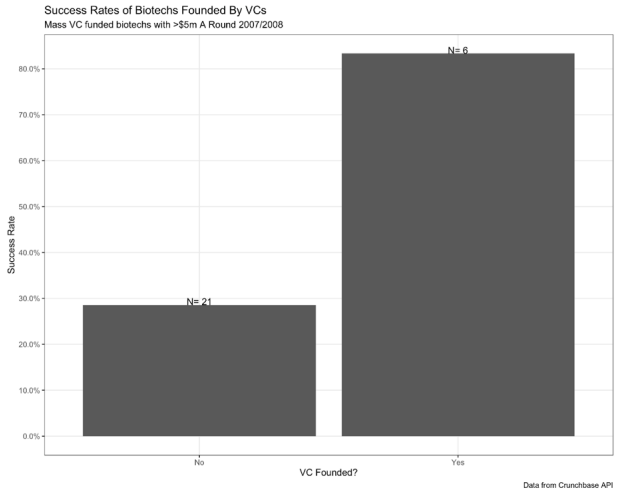
The venture creation model trend reflects that investors are learning, adjusting, and following the money. Looking back on the 27 A rounds of >$5M from 2007–2008, the subset of VC-founded companies had much better success rates. Of the six, five went on to have "successful" outcomes defined as IPO or acquisition (but not asset sale/bankruptcy or no documented exit), compared to less than 30% of the non–VC-founded companies (see Figure 3).

VC firms can follow each other's track records, and they may have seen that venture creation was paying off. Furthermore, VCs who pioneered the alternative approach got better at the process: systematically evaluating new science and ideas for commercialization, assembling experienced teams, and moving talented scientists/entrepreneurs between portfolio companies. Why would these VCs take chances on inexperienced external founders as their own rosters of trusted and accomplished entrepreneurs grew? And once the VC firm has the infrastructure to found new startups, why share the early equity in a syndicate?

Furthermore, historical exits in VC fail to support the classic VC model with its many deals and syndicate partners. In order to meet returns targets, VCs have to own a greater percentage of the company — requiring larger funds and less syndication (Bruce Booth 2012). But hasn't this always been true? Yes, but in earlier years, more VC investment came from diversified funds (not just biotech), so they relied on a standard model of syndication that was common in software/IT. Fund sizes were smaller until more recently, so they could not support taking up most of a A/B round themselves without betting a huge portion of the fund. In biotech, the combination of large capital requirements, few grand slam exits, and long timelines pose financing challenges relative to other industries.

That is not to say that VC's as incubators and founders will be the norm forever. This shift has occurred against the backdrop of a thriving US economy and exploding tech sector. As we discuss later, the venture creation approach has thrived within an ecosystem that is still largely operating as if venture dollars are distributed in the traditional way (to external startups).

Figure 3: Success Rates of VC-Founded Biotechs



F. Implications for the Biotech Startup Ecosystem

The evolution of biotech VC shows that that risk capital does not show up "fully optimized" to deliver for a nascent industry or technology. Learning curves, path-dependencies, and trial-and-error (of organizational forms) mean that the investment structure of the industry will evolve over time—even in highly competitive settings.

However, other players in the biotech ecosystem have largely continued to operate as though the traditional VC model was still dominant. The conventional logic is that academic entrepreneurs simply need support (research funding, technology resources, and mentorship)—and perhaps modest seed funding—to bridge the gap between scientific discovery and commercialization. But as we have seen above, the path from lab to market is changing, and would-be entrepreneurs, investors, and universities must adjust.

For "Scrappy" Entrepreneurs: The path for "scrappy" biotech startups is different, and especially in the age where the venture creation model dominates. The process is not about pitching VCs or making the (now rare) angel funding to VC transition. For academic scientists (graduate students, postdocs, and faculty alike), working with venture creation VCs to develop an idea can be a fabulous learning process and increase the chance of forming a company or landing a nice job with the VC. Those firms are more likely to put a venture in the hands of experienced executives than to give control to a first-time scientific entrepreneur.

But venture capital is not the only path available. The landscape of angel investors, government/non-profit funding, and corporate (pharma) partnerships can support exciting and novel work for "scrappy" founders. Rather than finding a "bridge" to VC financing, alternative paths require an understanding of how the venture would fit in with corporate buyers, and if the experimental scope is focused to survive smaller initial rounds. Smaller capital investment allows for more modest (but still rewarding) exits – and scrappy exits are of great interest to pharma; even an early deal with a heavily-funded, VC-founded firm will necessarily be very expensive.

For angel investors: Even well-capitalized angels can be stuck in no man's land. Angels spurn (poor quality) "leftovers," typically cannot fund clinical studies, and cannot get into the big syndicated follow-on deals for VC-founded biotechs. But they have high potential in serving academic entrepreneurs. By focusing on startups with clear pathways to early partnerships and corporate VC, angels can find solid returns and play an important role in the modern biotech ecosystem.

For government, foundations, and universities: Public/academic institutions can play a pivotal role in enabling scientific productivity and the transition from lab to marketplace. Government programs and grants should not merely "cream skim" and "top-off" the VC seeded/founded firms. They should double down on "Scrappyland," with the goal of corporate pharma exits (rather than VC transition) in mind. Providing gap funding to scrappy firms will save good ideas from languishing in funding purgatory, while encouraging scientists to bring potential high-impact solutions out of the academic lab. A good example of targeted "gap funding" is Cancer Research UK's Clinical Development Partnership (CRUK n.d.) a program designed to take compounds over the "valley of death" by running first-in-human clinical studies to generate critical value-creating proof of concept data. This program is a vehicle available to startup partners lacking the resources to run this first study, enabling the sponsor to take back the program subsequently to continue development (Mullard 2014).

Universities should be more active in getting biotech IP out of the lab. The current technology transfer process creates transaction frictions, and working with rookie entrepreneurs in academia is bumpier than with experienced entrepreneurs within the VC venture creation approach. Universities can grease the wheels of this tech transfer market better by making it easier for VCs to learn about IP within the university labs, and by enabling VCs to work with scientists within universities to translate science to startups in a way that fits the VC incubation model. In other words, we suggest that VC involvement in

universities move upstream—prior to polished pitches. VCs would have to commit credibly to not steal ideas, and scientists would have to accept less control over commercialization. Benefits would be earlier feedback and better sorting of ideas into the appropriate commercialization pathways.

Pitch competitions, university programs, and biomedical accelerators should focus on connecting and preparing scrappy scientist startups for these alternative funding sources and corporate buyers. How does a startup's intellectual property fit into established firms' portfolios? Such programs can help scientific founders match to corporate partners more efficiently and provide best information about paths to commercialization.

G. Lessons for Other Industries

Finally, the transformation of biotech VC may serve as an example to other "tough tech" industries with high uncertainty, large capital needs, and long time-to-market (e.g., clean energy, aerospace, next-generation computing). While less well-matched to the traditional (often impatient) VC approach, the societal returns from these technologies are potentially sky-high. Through experimenting with new modes of venture capital investing, biotech VC has shown how the organization of innovation can adapt to competitive technology environments, and find an alternative system that rewards investors while still generating novel companies. Whether the pendulum has swung too far towards venture creation and, if so, how this shift will affect other players in the biotech ecosystem is yet to be answered. But the boundaries between founders and financiers have been toppled.

Other "tough tech" industries should encourage similar experimentation with organizational forms. In these industries, creative capital allocation could mean adopting their own take on venture creation VC, creating specialized funds with more patient timelines (The Engine 2019) or working with academia to fund long-term research before moving to commercialization. What biotech VC has taught us is that the financing of innovation evolves to fit the technological problems, and that investors and founders should not assume that tomorrow's investment landscape will mirror the past.

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Chapter 4: Is the Impact of Corporate Venture Capital Meaningful for Venture Outcomes?

Abstract

Corporate venture capital (CVC) is a key tool large corporations use as a mechanism to externalize R&D, support targeted and relevant innovations, and seek returns for capital not otherwise used for internal investments or share buybacks. Accounting for 15% of venture investments, CVCs typically participate in the venture funding ecosystem alongside their institutional venture capital (IVC) peers (P. Gompers and Lerner 2000). CVC has been cyclical in popularity and scope, often following public market valuation trends. Lightly studied, CVC's impact on portfolio companies can be challenging to tease out. The shorter lifespans and cyclicality of the use of CVC suggests that the strategic benefits of CVC investments may be less profound, given that such effects would be long-term in nature and would require sustained effort. Using a large venture-investment focused dataset composed of 28,840 companies founded between 2000 and 2015 from Crunchbase, this study explores two potential effects by CVCs on portfolio companies: the probability of successful outcomes due to strategic input from the CVC to the portfolio company, and appropriation of innovation by the parent of the CVC via acquisition/merger of the target portfolio company. The results of the study show very modest increases in venture outcomes for CVC-funded companies — except for biotech firms, where the increase is more substantial. The timing of CVC activity (early or later rounds) does not appear to impact venture performance or M&A rates. In addition, the data do not show an impact on M&A rates for positive outcome ventures, putting into question whether the supposed appropriation process is meaningfully achieved.

A. Introduction and Literature Review

Large, research-intensive corporations regularly examine how best to optimize R&D investments – both how to organize internal R&D activities and how they might access various forms of external R&D. Methods to gain access to external R&D include, among others, licensing technology from universities and startups, embarking on collaborative research and joint development partnerships, acquiring R&D assets, and acquiring innovative startups (Chesbrough 2000). In the 1980s, we began to witness a significant level of activity in corporate venture capital (CVC), with large multinational corporations participating in the venture funding lifecycle through both limited partnership investments in institutional venture capital firms and direct investments into startups, often mediated through a *de novo* investment vehicle operated at some level of arm's length from the corporate parent. Early corporate venture capital efforts were clearly experimental, as no precedent data existed as to the positive effects that would accrue to CVC parent corporations.

CVC is a relatively new phenomenon, appearing in the latter decades of the 20th century. Only 15% of the invested venture capital flows from CVC investors, and CVC has historically been a thinly studied domain, with the majority of research in venture funding exploring institutional venture capital (P. Gompers and Lerner 2000). Research in the field has focused on a few key areas – foundational work describing CVC, developing theoretical models to explain CVC behavior, explorations of benefits that accrue to CVC portfolio companies, and studies of benefits accruing to the parent company of the CVC. Dushnitsky, for example, documents that CVCs invest more aggressively in later-stage entrepreneurial ventures and articulates that a key motivation is "spotting potential acquisition candidates" (Dushnitsky 2009). Only 98 peer-reviewed, English-language articles were published in the field through 2015 (Röhm 2018).

Motivation for embarking on CVC venturing is typically split into two distinct categories – strategic and financial return (Dushnitsky 2009). Strategic returns include both absorbing new, innovative technologies as well as other potential spillover benefits. The latter include human resource/management benefits accruing to managers, related recruiting benefits of potential new employees, achieving a window on new technology, and stimulating complements.

Dushnitsky & Shaver explore the role of the strength of various industry-specific IP regimes on the CVC–entrepreneurial company relationship, arguing that CVC activities will be more robust and sought after when IP regimes are strong, thus protecting the startup (Dushnitsky and Shaver, 2009). One example of the CVC phenomenon stems from the period of 2003–2010, during which Biogen Idec formed $200m biopharma CVC as a direct result of the merger between Biogen and Idec. This CVC focused on the biopharmaceutical space and was led by a former senior executive of Idec post-merger. The fund participated in 18 investments over its life but did not originate or lead any of these deals; instead, it participated alongside a set of IVC investors. As a consequence of a senior management transition (a new CEO came on board) the fund was shut down on the basis of the new CEO's negative view on the value of CVC activities apart from traditional business development processes. With little connection between the CVC fund activities and portfolio companies with Biogen's internal R&D team, there was no ongoing strategic inertia to provide continued support for the CVC effort following the leadership change.

This example helps formulate a key question – do CVCs have important and recognized positive impacts on their corporate parents? One way to look for impact is to explore the phenomenon of CVC parents acquiring some percentage of their portfolio companies by internalizing the technology developed

externally, with some corporate capital supporting this development. Across a broad set of startups, positive exits include both IPOs and acquisitions. For the subset that receive CVC, we might expect that the rate of acquisition would be higher if this CVC parent acquisition process is indeed happening.

Why Are CVCs so Cyclical and Short-lived?

A key early paper on CVC by Gompers and Lerner argues that CVC investments are not inferior to institutional VC (IVC) investments on the basis of performance. However, the paper observes that CVC programs are typically much shorter-lived than IVC funds – although those with a clear strategic focus can be as long-lived as their IVC peers. The authors identify three common causes for the early demise of CVC funds: poorly defined missions (strategic vs. financial), insufficient commitment to the CVC initiative, and CVC partner/leader compensation schemes. They explored a dataset of 32,364 CVC and IVC investments between 1983 and 1994—8506 of which were CVC investments—and argue that strategic CVC investments lead to significantly better outcomes (IPO/M&A; (P. Gompers and Lerner 2000).

In spite of this potentially positive impact, CVC has also been a highly cyclical activity. Chesbrough discusses a historical perspective of CVC, examining the cyclical nature of CVC initiatives in the 1960s through the 1980s. In the early days of CVC, 25% of the Fortune 500 ran CVC initiatives, most of which were disbanded in the '70s and then re-initiated in the '80s, alongside the strong growth of institutional venture capital. But once again, during the downturn of 1987, many CVC funds were disbanded (Chesbrough 2000).

A related paper by Chesbrough articulates a model for understanding different categories of CVC investments — driving, enabling, emergent, and passive ones. These differ on two dimensions: objective (strategic vs. financial) and linkage to the CVC parent operational capability (strong vs. weak). This model attempts to explain why many CVC initiatives are so transient and susceptible to shutdowns in weak markets: passive investments linked weakly to the CVC parent are the most vulnerable to cyclicality, whereas emerging and driving investment motivations lend more long-term stability to CVC initiatives (Chesbrough 2002).

Some authors explore the conditions under which CVC seems to be more active. Da Gbadji, Gailly, and Schwienbacher (2015) examine the rationale for large corporations across multiple geographies to embark in CVC activities and the local conditions under which they thrive. The authors argue that local conditions that are favorable to entrepreneurship and have lower cost personal bankruptcy regulations support more active CVC activities (Da Gbadji, Gailly, and Schwienbacher 2015).

These observations of cyclicality and short lifetimes provoke an important question – why is CVC activity so cyclical and short-lived if the benefits to CVC parents are strong? The intriguing consequence of this line of reasoning is that perhaps such benefits to the CVC parent are not in fact as dramatic.

Benefits to the Portfolio Company

One of the key challenges in studying the CVC field empirically is that CVCs typically invest alongside institutional venture capital (IVC) firms, and there are few startup firms that have received CVC without IVC. Consequently, disentangling the variation in outcomes due to CVC and IVC is a common challenge faced across much of the literature. In addition, separating observed differences in outcomes for CVC-funded companies suffers from significant selection bias: are we measuring the investing skill of passive

CVC investors or the incremental beneficial results of active CVC investors having a positive impact on their portfolio companies?

CVCs typically invest alongside IVC investors, and they usually own a much smaller share of equity than do the IVCs. It is rare that CVCs invest alone, so disentangling the effects of CVCs on portfolio companies is both challenging and subject to significant selection effects. For example, if high-prestige CVCs only select companies to invest in that already have participation by top IVCs, observed superior outcomes may be mediated more by selection than active participation/strategic contribution of the CVC.

Hellman develops a model to describe the dynamic choice entrepreneurs make in selecting CVC or IVC. Focusing on the potential strategic benefits that could accrue to the portfolio company by CVC investment, the model seeks to describe why entrepreneurs may rationally select CVC vs. IVC investors based on the nature of the business complementarity/substation/threat to the CVC (Hellmann 2002).

Through the framework of institutional logics literature, Pahnke et al. examine a set of 198 MIS (minimally invasive surgical) device firms over 22 years (1986–2007). They conclude that due to institutional logic constraints, CVC investors provide less help to startups than IVCs, although CVCs provide 1/3 of all VC funding in the dataset examined. The outcomes were focused on technology innovation (patents) and commercial innovation (product approvals) (Pahnke, Katila, and Eisenhardt 2015).

Park and Steensma, who explored a sample of 508 computer, semiconductor, and wireless ventures from 1990–2003, argue that CVC provides access to complementary assets but may constrain startups (competition). They also find data to support the idea that CVC-backed startups are more likely to have an IPO; they are also less likely to fail (Park and Steensma 2012).

Ginsberg et al. (2011a) discuss the impact of CVC on portfolio companies, with a specific focus on the IPO process and the prestige of underwriting banks. They examined 1,830 IPOs of VC-backed companies, 315 of which had at least one CVC investor with >5% equity. They also counted the number of CVC investors in each company, and noted when the CVC was a bank, a member of the S&P500, and in the same industry as the portfolio company. This study showed that CVC investors did lead to more prestigious underwriters; however, number of CVC investors did not increase the effect. The participation of a bank-CVC also had a positive effect on underwriter prestige, which membership in the S&P 500 did not. The mechanisms offered for this effect are a combination of screening/selection by the CVC and consequent signaling effects that benefit the portfolio company through its IPO process (Ginsberg, Tucci, and Hasan 2011).

Ginsberg et at (2011b) explored the same set of 315 IPOs with CVC investors, focusing on the discount of IPO price reductions associated with investors who are bank CVCs or S&P500-listed (i.e. prestigious) CVCs and argue that certification signaling effects provide a reduction in the discount of IPO pricing due to CVC know-how and prominence (Ginsberg, Hasan, and Tucci 2011).

Fulghieri and Sevilir extend upon Hellman's model to develop additional models of the choices of a large company engaging in CVC activities and the choice of startups to select financing from CVC and IVC investors. They specifically predict that startups funded by CVC have a higher probability of being acquired by the CVC's parental firm (Fulghieri and Sevilir 2009).

Chemmanur, Loutskina, and Tian argue that CVC-funded firms are more innovative (as measured by patent production and quality) than IVC funded firms. CVCs invest in younger, riskier, and less profitable firms. The authors argue that two characteristics of CVCs enable these results – technological fit and greater failure tolerance (Chemmanur, Loutskina, and Tian 2014). In a similar fashion, Alvarez-Garrido and Dushnitsky use a dataset of 545 biotech firms to also argue that CVC-backed firms are more entrepreneurially productive, as measured by patenting activities, particularly when industry sectors or geographic locations are aligned between CVC parent and CVC portfolio company (Alvarez-Garrido and Dushnitsky, 2016).

One specific way CVC investors may have positive impacts on their portfolio companies is to increase the probability of a successful venture exit. Mechanisms that CVCs might employ to support their portfolio companies include providing access to resources, leveraging internal and external networks, and setting up collaborations between the CVC parent and the CVC portfolio company. If these kinds of activities do in fact support the CVC portfolio company in a meaningful way, we should expect to see higher success rates based on exits (M&A and IPO outcomes) in CVC-funded firms.

H1: CVC-funded firms (i.e., firms with CVC & IVC funding) will have higher success rates (IPO or M&A) than their IVC-only funded peers.

This paper contributes to the field by exploring both expected impact of CVCs on their portfolio companies by examining venture outcomes and the expected benefit to CVC parents by examining M&A rates. In addition, as most studies in the field work with very small, bespoke datasets, this study contributes by examining a large and broad dataset of 28,840 companies. Finally, this paper looks closely at industry differences; in particular, it isolates biotech and technology firms with their unique capital requirements and venture characteristics, thus providing a novel approach to exploring the impact of CVC investments.

Biotech firms are more capital intensive, typically have much longer product development lifecycles, and can spend many years without any revenue. In contrast, technology firms typically have much lower capital requirements, have more rapid product development timelines, and can achieve revenue within a few years of founding. Based on these differences, the potential impact on capital from CVCs may be more important in the more capital-intensive biotech sector; however, we might expect that tech company CVCs would be able to make acquisition decisions on their portfolio companies more rapidly, due to the shorter product development and time-to-revenue timelines.

H1a: Biotech firms funded by CVC will demonstrate higher success rates than tech firms funded by CVC.

H1b: Tech firms funded by CVC will demonstrate higher M&A rates than biotech firms funded by CVC.

Benefits to the CVC Parent

A key potential benefit of CVC activity is strategic to R&D, as the positive effect of outsourcing R&D (through CVC investments) should be the absorption/acquisition of novel technologies and innovations. Chesbrough, Tucci, and van de Vrande explore the associations between CVC programs in large companies and both their R&D budgets and corporate valuation. They examined a set of 270 public companies engaging in CVC investments between the years 1973 and 2000. The authors observe a correlation between R&D spending and CVC activity, and that a combination of higher R&D spending

and CVC activity is associated with better firm performance. The study is limited in both the size of the dataset explored and the time period, as the growth in CVC was substantial beginning in the early 2000s. Ultimately, the study is not able to observe if actual positive R&D effects are occurring as a result of CVC activities.

Benson studied a set of 34 CVCs that acquired 242 startups and examined their returns. The study supported theoretical predictions stemming from the absorptive capacity literature, observing that returns were inversely related to the ratio of CVC investment / R&D expenditures and that consistent, long-term CVCs outperformed the competition. In this "event study", performance was measured by the market reaction to acquisition announcements. The authors estimate the optimal amount of CVC investment as a proportion of overall R&D spending to be 13–15% (Benson and Ziedonis 2009).

Other potential benefits to the CVC parent are discussed by several authors. Chesbrough addresses a novel goal highlighted from more recent (i.e., 1990s) CVCs – that of motivating employees to behave in more entrepreneurial ways. In this paper, Chesbrough highlights key differences between CVCs and IVCs, exploring both internal characteristics and operational strengths and weaknesses. A key argument presented in this paper is that for a CVC to succeed in a world with dramatically increased IVC, it must offer "structural advantages" to startups: potential longer investment timespans, larger scale, the ability to learn from mistakes, and the ability to inject domain expertise and other corporate resources alongside the capital (Chesbrough 2000).

De Bettignies and Chemla also discuss how CVC activities could benefit CVC parent HR activities through the development of a model to explore two distinct benefits CVC activity can bring to the parent organization — both higher returns and better recruitment potential for managerial "stars." In this model, CVCs (at least during periods of high market returns) help their parent organization attract and retain high-quality managers (De Bettignies and Chemla 2008).

Masulis and Nahata show that acquiring CVC-backed firms leads to higher acquirer returns, due to increased pressure by the CVC to exit more quickly. In their sample of completed acquisition, 337 firms completed deals with VC backing, compared to 2452 deals with no VC backing. Sixty of the 245 VC-backed targets include CVC investors, and 57 are "strategic" based on a variety of criteria to define an operating relationship (Masulis and Nahata 2011). Dushnitsky argues that CVC-backed startups experience favorable performance compared with peers funded by IVC investors alone (Dushnitsky 2009).

Dushinisky showed that benefits to CVC parents appear to be sector specific. In his 2006 study, he explicitly identifies the devices and information sectors according to where the most CVC parental benefits appear (Dushnitsky and Lenox 2006).

One way strategically focused CVCs can meet their strategic goal of externalizing R&D is to ultimately internalize this new R&D through the mechanism of a strategic acquisition of the portfolio company. We can therefore hypothesize that strategic CVC investors may at times acquire their portfolio companies when there is a particularly strong strategic fit between the emerging company and the parent. If true, we should expect to see an increased rate of M&A outcomes for CVC-funded companies compared to the IVC-only funded peers.

H2: CVC-funded firms (i.e., firms with CVC & IVC funding) are more likely to be acquired compared to their IVC-only funded peers.

B. Data Source and Analytic Methodology

Data Source

This study analyzes a dataset from the Crunchbase online venture funding website, which is made available under a research license provided to academics. Downloaded on September 20, 2018, the complete dataset incorporates data from funding rounds (228,786), companies (644,893), investors (107,838), and exits in the form of initial public offerings (16,516) and merger/acquisition (80,084). The rounds dataset covers a large range of years (1968-2018), with the data concentrated from 2000-2018 (see Table 1).

Table 1: Rounds/Year

Year	Rounds/ Year
1968-1998	890
1999	1,234
2000	4,215
2001	1,781
2002	1,700
2003	1,885
2004	2,340
2005	3,084
2006	3,906
2007	5,428
2008	5,834
2009	7,397
2010	9,970
2011	12,278
2012	15,413
2013	20,319
2014	26,215
2015	28,876
2016	29,011
2017	28,231
2018	18,779

The Crunchbase dataset covers a broad geographic range of companies, including the US and Europe, with 90% of the firms located in 17 countries (see Table 2).

Table 2: Companies by Country

Country Code	N	Percent
USA	227,779	35.3%
Missing	187,385	29.1%
GBR	38,553	6.0%
IND	23,710	3.7%
CAN	18,905	2.9%
DEU	11,913	1.8%
FRA	10,947	1.7%
AUS	10,704	1.7%
CHN	8,719	1.4%
ESP	8,471	1.3%
NLD	5,943	0.9%
ISR	5,451	0.8%
CHE	5,310	0.8%
BRA	5,189	0.8%
IRL	4,336	0.7%
SWE	4,336	0.7%
ITA	4,213	0.7%
SGP	3,653	0.6%
Total	585,517	90.9%

The Crunchbase dataset is assembled from a diverse set of source material including press releases, SEC filings, and self-reported data. The database is structured to document startup companies, their multiple funding rounds, and the investors participating in each round, as well as IPO and M&A activity when appropriate.

Several limitations in the Crunchbase dataset stem from the data collection approach taken. Investor lists per round may be incomplete, missing smaller investors and some or all angel investors participating (although a large number of angel investors and investments are included in the dataset). Round totals are estimated, but the specific participation level (i.e., dollars invested) from each investor is not typically available. Crunchbase provides an investor table and codes each as one of 28 distinct investor types (i.e., angel, VC, accelerator, corporate VC).

Data Selection

From the broad Crunchbase dataset, this study examines a subset of firms founded between 2000 and 2015, based in the US, with at least 1 investment round and a defined industry code. The Crunchbase dataset shows dramatic increases in data quality after 2000; the dataset founding date is terminated at the end of 2015 to provide a window of time for new firms to develop a funding pattern. We expect that the newest firms may show lower exit rates. This is due to their youth, which may bias the entire dataset down somewhat in this respect. Thus, the sample might exhibit some right censoring.

Coding Methodology

Investors are grouped into 4 categories (VC, corporate VC, angel, and other/unknown). Each round, all of which have one or more investors, is coded as follows, where IVC = institutional venture capital and CVC = corporate venture capital.

Round Investors	Code
Unknown	u
IVC only	i
CVC only	c
CVC + IVC	v
Angel and no VC	a
Angel + IVC + CVC	b
Angel + IVC	d
Angel + CVC	e

Subsequently, each company receives time-ordered string of investment round codes. Examples are "aac" for a company with three funding rounds, the first two of which were angel rounds and the 3rd a corporate venture capital round, and "iv" for a company with two funding rounds, first an institutional venture round followed by a round with both institutional and corporate VCs. Finally, the time-ordered strings are analyzed to code each company with a single investor type code that summarizes the investor type history:

CODE	Explanation
A0VC	Angels but not VCs
A2CVC	Angel first then CVC (but no IVC)
A2IVC	Angel first then IVC (but no CVC)
A2VC	Angels first then both IVC and CVC
CVC	CVC only, no pure angel rounds
IVC	IVC only; no pure angel rounds
VC	IVC and CVC, no pure angel rounds

These codes capture important differences in funding history. Companies may start with angel funding or may move immediately to venture funding; these codes also separate out various combinations of institutional and corporate venture capital in a manner that allows for outcome attribution by investor coding.

Under the assumption that CVC investment may be associated with differential outcomes in either or both the portfolio company and the CVC parent, we could hypothesize that such effects might be more pronounced in companies that have CVC investors earlier compared with ones where CVCs participated in later rounds only.

H3: CVC-funded companies that received CVC early in their funding cycle will show more significant positive effects on portfolio company success compared to firms receiving CVC later in their funding cycle.

H4: CVC-funded companies that received CVC early in their funding cycle will be more likely to be acquired.

To explore this hypothesis, companies that raised capital from CVCs were coded as CVC_EARLY if a CVC participated in their first VC round, or, when there were at least 4 VC rounds, a CVC participated in the second round. Companies were coded as CVC_LATE if a CVC participated in the last VC round, or, when there were at least four VC rounds, a CVC participated in the second-to-last round, and there were no early CVC investors. This coding of CVC_EARLY and CVC_LATE allows for grouping the companies into two groups — one that raised CVC early and the other that did so in later rounds.

Outcome coding

As is common in the literature, each company is coded as a success if there is a record of the firm undergoing either an IPO or merger event; otherwise the company is coded as not (yet) being successful.

At the group level, a novel outcome statistic is calculated — the M&A to IPO ratio, which is calculated for a set of companies as the number of M&A exits / (number M&A + number IPO). The purpose of this metric is to look at how common the M&A exit path is for a group of companies, and to explore whether corporate venture capital participation acts as a modifier for this metric. If one of the key strategic goals of corporate venture investors is to externalize R&D, then we might expect that in some successful cases, the corporate investor would like to internalize the newly innovated technology, and may do this through an M&A transaction. If this is a meaningful pathway, we should expect to see an increase in M&A exits and M&A exit rates.

C. Data/Findings

Descriptive statistics

Table 3 shows summary statistics of the full dataset used in further analysis – companies founded from 2000-2015, in the US, with industry coded, and at least one angel, IVC, or CVC funding round.

Notable observations include the following:

- Only approximately 10% of companies in this dataset received CVC funding, significantly lower than the 15-20% typically reported in the literature.
- CVC-funded companies have more funding rounds, are more commonly in the biotech or tech fields, and are more typically present in venture capital "hub" states (MA, CA, NY, TX, IL) where the highest concentration of venture investing takes place.
- CVC-funded companies have more employees.

Differences between US and non-US companies are illustrated in the Appendix, with similar trends seen in the non-US dataset. For the rest of this paper, we will focus on US-based companies.

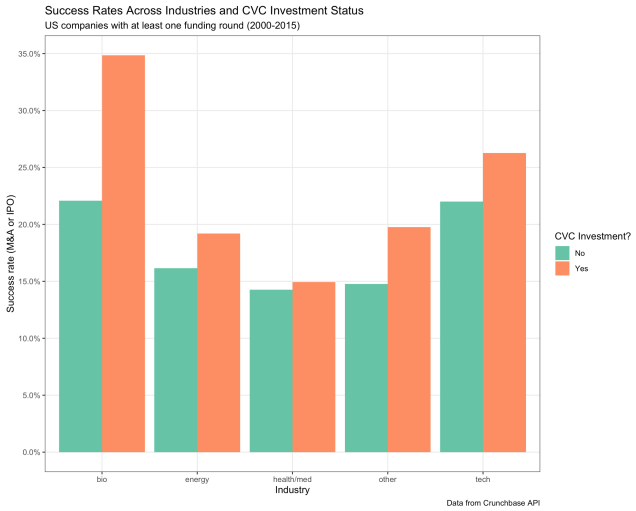
Table 3: Summary Statistics

	CVC funded (N=7553)	No CVC funding (N=21287)	Total (N=28840)	p value
funding_total_usd				< 0.001
N-Miss	506	4524	5030	
Mean (SD)	62,170,109.3 (375,910,851.0)	17,943,869.8 (58,267,272.9)	31,033,425.1 (211,226,293.3)	
Range	1700.0 - 22212450000.0	1000.0 - 2295000000.0	1000.0 - 22212450000.0	
funding_rounds				< 0.001
Mean (SD)	3.7 (2.5)	2.3 (1.8)	2.7 (2.1)	
Range	1.0 - 28.0	1.0 - 43.0	1.0 - 43.0	
industry				< 0.001
bio	885 (11.7%)	1755 (8.2%)	2640 (9.2%)	
tech	4831 (64.0%)	12892 (60.6%)	17723 (61.5%)	
other	1837 (24.3%)	6640 (31.2%)	8477 (29.4%)	
vchub				< 0.001
no	1989 (26.3%)	7326 (34.4%)	9315 (32.3%)	
yes	5564 (73.7%)	13961 (65.6%)	19525 (67.7%)	
employee_count				< 0.001
N-Miss	68	177	245	
1-10	1424 (19.0%)	7833 (37.1%)	9257 (32.4%)	
11-50	3017 (40.3%)	7730 (36.6%)	10747 (37.6%)	
51-100	1130 (15.1%)	1918 (9.1%)	3048 (10.7%)	
101-250	728 (9.7%)	810 (3.8%)	1538 (5.4%)	
251-500	327 (4.4%)	462 (2.2%)	789 (2.8%)	
501-1000	192 (2.6%)	401 (1.9%)	593 (2.1%)	
1001-5000	102 (1.4%)	175 (0.8%)	277 (1.0%)	
unknown	565 (7.5%)	1781 (8.4%)	2346 (8.2%)	

CVC Effect on Venture Outcomes

Exit success at the portfolio company level is defined here as an observed initial public offering (IPO) or merger/acquisition (M&A) event. Success rates are calculated at the group level by totaling "successes" (IPO or M&A) / total in the group. Chart 1 shows success rates grouped by portfolio company (not CVC parent) industry. Companies with CVC funding show only modest increases in positive outcomes. The notable exception is biotech firms, whose success rates rise dramatically from 22% to 35%.

Chart 1: Portfolio Company Success Rates by Industry



H1 is modestly supported in this dataset across most industries, and it is strongly supported in biotechnology. However, in the regression model below as presented in Table 4, the impact of CVC on exit outcomes was not significant.

H1a posits higher exit rates for biotech vs. tech firms when both are funded by CVC. Although there are slightly elevated rates seen in Chart 1, this increase is not shown to be significant in the regression in Table 4.

M&A Rates in CVC-funded Portfolio Companies

A second outcome statistic is calculated for successful companies in the dataset — the "M&A rate," which is defined as the number of companies exiting through M&A / all companies with a successful exit (IPO or M&A). Higher portfolio company M&A rates point to two potential benefits to CVC-parents: higher financial returns to the parent and the possible acquisition of the portfolio company technology.

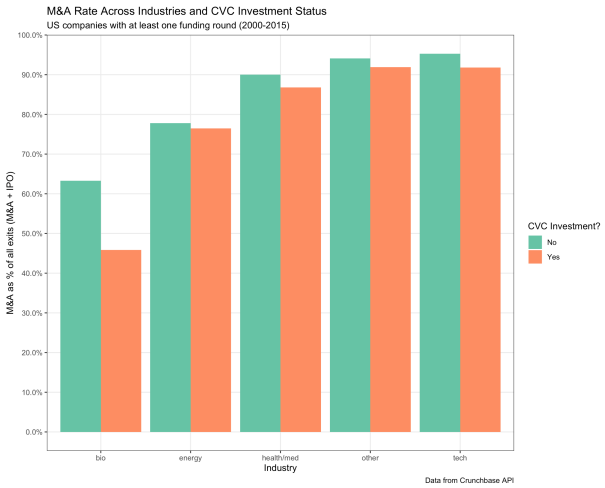
One of the key drivers for large companies to create CVC operations is a strategic goal to externalize R&D. However, for this goal to be realized, R&D will ultimately need to be incorporated back into the corporate parent — a specific mechanism of technology appropriation and absorption. The multiple mechanisms that a CVC parent can use to incorporate external technology include licensing and joint ventures, but certainly acquisition is one potentially significant mechanism. CVCs will often have board representation or observer status, which can be used this to track potential acquisition targets, inform the parent of portfolio company progress, and serve to facilitate business development discussions that could lead to a transaction. Overall M&A rate is certainly an indirect measure — and positive increases

do not confirm that the parent acquired its own portfolio company. However, under the assumption that at least some CVCs will acquire their portfolio companies, we should see an increase in the rate if such M&A activity is occurring at a meaningful rate.

However, the data do not support this hypothesis (H2). Across all industry groups, the M&A rate is unchanged for companies receiving CVC versus those that do not, suggesting that CVC activities may not in fact lead to increased internalization by this method. A structural weakness beneath this conclusion is that we are only looking at incremental M&A activity and not at other mechanisms for potential technology appropriation/absorption — i.e., licensing and other forms of parent/portfolio company partnership.

H1b asks if M&A rates are higher for tech firms funded by CVC as compared to biotech firms funded by CVC. In Chart 2 we do see higher M&A rates for tech firms compared to biotech firms, and the regressions in Tables 4 and 5 also support this hypothesis.

Chart 2: M&A Rates



Regression Analysis – Drivers of Venture Success

To explore the potential drivers of venture success further, each company was coded for the following funding observations: angel funding, presence of CVC, and presence of IVC. Additional control variables included were: amount of funding, number of rounds, industry, and presence in a VC hub. A logistical regression was performed as follows:

success_ind ~ a_founded + vc_funded + cvc_funded1 + funding_total_m_usd + funding_rounds + vchub + industry_type

CVC funding status (i.e., whether or not the firm received CVC funding) is the only insignificant independent variable in this model once all controls are in place. This regression supports the conclusion that the participation of CVC investors does not impact venture success. A second regression was performed with M&A as the dependent variable, and again CVC funding status was not significantly associated with M&A outcomes.

Table 4: Logistic Regressions

Logit Regression on Success & Aquisition

	Dependent variable:	
	Successful Exit	Acquisition
	(1)	(2)
a_founded	-0.594*** (0.051)	-0.482*** (0.053)
vc_funded	0.825*** (0.062)	0.945*** (0.065)
cvc_funded1	0.015 (0.036)	0.047 (0.038)
funding_total_m_usd	0.0002* (0.0001)	-0.0005** (0.0002)
funding_rounds	0.060*** (0.008)	0.007 (0.009)
vchubvchub_yes	0.245*** (0.036)	0.234*** (0.037)
industry_typeenergy	-0.495*** (0.131)	-0.021 (0.148)
industry_typehealth/med	-0.541*** (0.089)	0.050 (0.099)
industry_typeother	-0.393*** (0.062)	0.228*** (0.071)
industry_typetech	-0.026 (0.051)	0.614*** (0.061)
Constant	-2.036*** (0.079)	-2.708*** (0.088)
Observations	23,810	23,810
Log Likelihood	-12,156.480	-11,424.840
Akaike Inf. Crit.	24,334.960	22,871.680
Note:	*p<0.1; **p<0.05; ***p<0.01	

Given that we are able to describe the entire longitudinal pattern of investment for each company in the dataset through coding each investment round by the type of investor, it is possible to group CVC-funded portfolio companies into two sets – those that received CVC in early rounds, and those that did not, but did receive it in later rounds. If CVC involvement has an impact on their portfolio companies (improvement in venture outcomes; increases in M&A rates), then we might expect to see this effect amplified in companies with longer (earlier) exposure to CVC.

A regression was performed looking at the endpoints of successful exit and M&A rate as dependent variables and early/late CVC as the key independent variable. Control variables for funding amount total, number of rounds, geographic presence in a VC hub state, and industry were included in the model. This result showed a very modest but not significant impact of timing of CVC to both outcomes, so Hypotheses H3 and H4 are not supported in this dataset.

Table 5: Regression on Early/Late CVC Investment

Logit Regression on Syccess & Aquisition

	Dependent variable:	
	Successful Exit	Acquisition
	(1)	(2)
cvc_late_earlycvc_late	0.017 (0.065)	0.035 (0.069)
funding_total_m_usd	0.0001 (0.0001)	-0.0004 (0.0003)
funding_rounds	0.025* (0.014)	-0.042** (0.017)
vchubyes	0.212*** (0.080)	0.124 (0.084)
industry_typeenergy	-0.833*** (0.252)	0.035 (0.282)
industry_typehealth/med	-0.952*** (0.202)	-0.003 (0.219)
industry_typeother	-0.684*** (0.124)	0.274* (0.144)
industry_typetech	-0.398*** (0.095)	0.521*** (0.118)
Constant	-0.756*** (0.128).	-1.417*** (0.151)
Observations	4,649	4,649
Log Likelihood	-2,785.370	-2,566.543
Akaike Inf. Crit.	5,588.740	5,151.085
Note:	*p<0.1; **p<0.05; ***p<0.01	

In most cases, CVCs invest alongside IVCs, so it can be challenging to disentangle portfolio company effects, due to the various investor type. Our coding of each round for each portfolio does enable grouping of portfolio companies by the investor types involved.

Table 6 illustrates success rates for various groups (again, with success defined as either M&A or IPO). A0VC represents companies with angel investors only (but not IVC or CVC investors); A2CVC represents initially angel-funded companies that later raised CVC (but not IVC). A2IVC similarly represents initially angel-funded companies that later raised IVC but not CVC. A2VC represents initially angel funded companies that later raised both CVC and IVC. These three groups are repeated for companies that did not initially raise angel funding (CVC, IVC, VC).

We see that across all industry sectors, exclusively CVC-funded companies perform more poorly than their IVC-funded peers. There may be strong strategic reasons that CVCs make the less common "exclusive" investments, but it is clear that these firms have weaker exit rates.

Table 6: Success Rates by Funding Category and Industry

Funding Pattern	Bio	Energy	Health/Med	Other	Tech
Angel, no VC	5.5%	3.3%	5.2%	5.8%	9.7%
Angel then CVC	20.0%	0.0%	0.0%	18.5%	12.5%
Angel then IVC	9.8%	10.0%	5.4%	17.4%	18.6%
Angel then both IVC & CVC	18.8%	8.3%	9.4%	22.9%	20.3%
CVC only	17.1%	13.2%	8.0%	10.7%	14.0%
IVC only	30.7%	20.9%	19.7%	20.3%	28.6%
CVC & IVC only	36.5%	26.2%	19.0%	25.2%	30.6%

Proximity to portfolio companies appears to affect a number of venture outcomes, and geographic concentration of both startups and venture investors in hubs (Silicon Valley for tech startups and Cambridge, MA, for biotechs) is clear. Presence in a hub state is defined here as location in the states with the largest number of venture-invested portfolio companies (MA, CA, NY, IL, and TX). We can explore if we see different results for CVC portfolio companies in either VC-hub states or outside these.

Success rates are calculated for both VC hub–based companies and companies based outside VC hubs. The crosstab below shows convincingly that overall success rates for portfolio companies are modestly higher for those based in VC-hub states than other states, as expected, with a stronger positive signal in VC-hub states, as shown in Table 6.

Table 7 – Portfolio Company Success Rates In VC-hubs

VC Hub State?	No CVC	Has CVC	Fold Increase with CVC
Non-VC-State	16.5%	20.5%	124.6%
VC-state	21.4%	27.2%	126.6%

D. Discussion

This study examines a large, broad set of funded firms founded between 2000 and 2015. In contrast to themes commonly observed in the literature, this study does not show significantly better outcomes for CVC-backed firms compared to IVC-backed firms. Expected enhancement of M&A rates is also not seen in the CVC-backed subset. In addition, extended "exposure" to CVC – early investment by CVCs – compared to lower/later exposure does not show any differential effects. These results question some of the fundamental assumptions underpinning CVC activities.

Summary: Hypotheses and Findings	
H1: CVC-funded firms will have higher success rates (IPO or M&A) than their IVC-only funded peers.	Modestly supported in most sectors; stronger effect in biotechnology sector
H1a: Biotech firms funded by CVC will demonstrate higher success rates than tech firms funded by CVC.	Not able to reject the null hypothesis
H1b: Tech firms funded by CVC will demonstrate higher M&A rates than biotech firms funded by CVC.	Supported
H2: Companies that receive CVC investment are more likely to be acquired, compared to their IVC-funded peers.	Not able to reject the null hypothesis
H3: CVC-funded companies that received CVC early in their funding cycle will show more significant positive effects on portfolio company success.	Not able to reject the null hypothesis
H4: CVC-funded companies that received CVC early in their funding cycle will be more likely to be acquired.	Not able to reject the null hypothesis

Although contrasting with some published studies, these results are consistent with both broad as well as specific observations. The significant cyclicality of CVC activities poses a challenge to the practice. If it truly is an important source of appropriable technology and a valid mechanism for R&D externalization, then we might be surprised to observe such strong public-equity market sensitivity. Arguably, such investments are more valuable at times of resource constraint compared to internal R&D, as external investments are much more easily titratable without expensive and demoralizing layoffs.

A related point is that for many CVCs, especially those with financial vs. strategic motivations, high walls are established between the CVC operation and the CVC parent R&D team. Such walls are perceived as a benefit for the portfolio company, as they allow for the preservation of confidentiality and the potential to conduct a true arm's-length negotiation in the future. Novartis Ventures, a child entity of Novartis, is an excellent example of a financial investor in the biotech field that maintains a very high wall between portfolio companies and parent R&D activities. Such rigorously financial (vs. strategic) investors, though born from parental capital, appear to act and behave as their IVC peers.

There is in fact a natural tension and potential conflict of interest in the CVC governance relationship with the portfolio company (Dushnitsky and Lenox 2006). To the extent that a CVC investor plays a

board role with the portfolio company, the conflict is between the desire of the parent to appropriate R&D innovation and the portfolio company to maximize the value of its innovations. To the extent that a CVC is playing a purely financial role, then incentives are aligned with the portfolio company (but not to the parental CVC), and we should not be surprised if the parent does not benefit beyond financial gain. Similarly, if the CVC has a strong strategic focus, then the CVC board representative is more clearly conflicted and may be recused for any of these activities, once again minimizing the potential strategic benefit that could accrue to the parent.

It is worth thinking more carefully about possible motivations for large corporations to launch CVC activities. These motivations are commonly split into the well-documented duality: financial return and strategic return. However, given both the relatively short life cycles of CVC activities and the tenure of senior management leaders of these activities compared to the length of a typical IVC fund (10 years is typical), it may be difficult for large corporations to build institutional memory and expertise in operating CVC funds. We might expect to see outperformance in the portfolios of financially focused CVC investors in the form of more exits, higher rates of IPO, and higher post-IPO valuations, while the strategically focused CVC investments might experience higher M&A rates.

Also, compensation constraints are a significant potential problem for CVCs, as talented CVC management will likely earn much less inside a corporate CVC than by leaving the corporate parent to join an IVC fund lacking such compensation constraints — thus creating a negative incentive acting against developing a skilled, long-term CVC team. These dynamics argue for the view that CVC teams may lack top-tier investing expertise and instead typically follow IVC lead investors and participate alongside top-tier IVC syndicates. Such follower behavior may evidence less investment outperformance and may simply allow CVCs to perform at a similar level to their IVC peers.

If CVC activities in fact provide little or no significant strategic benefit, then why do large corporations participate at such high levels? Signaling benefits may help provide a more consistent answer. By simply running an active CVC, the CVC parents may benefit by being seen as an active “player” in the startup community. Spillover benefits may accrue to other external innovation activities, including licensing and partnership deal-making. It may be challenging to attribute BD success to CVC activities, in particular when the BD activities involve target companies outside the CVC portfolio. Effectively, participation in CVCs may be an expensive branding exercise to demonstrate participation in the early stage ecosystem.

Another reason CVC are undertaken may be associated with the career ambitions of CVC-initiating leadership inside the corporate parent. CVC investing is a high-prestige activity that offers investors access to the entrepreneurial and IVC communities, intellectual stimulation that may be broader and more diverse than what is experienced inside the parent, and perhaps an important role in the corporate career development ladder.

The larger outcome benefits seen by CVC-funded biotech firms are interesting, but they are difficult to disambiguate without further study. Some possible explanations stem from unique characteristics of biotech ventures – very high capital requirements, high risk, and long-time frames until value creation. CVC participation in biotech ventures and its association with better outcomes (M&A + IPO) may first of all be a selection effect. If CVCs choose well in this field (either through syndication with top-tier biotech venture funds or through strong venture selection), then they may see better outcomes. A second possible explanation could be that the additional capital from CVCs is more critical to the outcomes of biotech firms, given their high demand for capital.

E. Conclusions and Future Research Opportunities

The Crunchbase database provides a very broad dataset with funding detail that can be described longitudinally by investor type, thus creating a novel venture metric offering analytic detail previously unavailable. Coupled with demographic and outcome data, this dataset enables exploration of a range of questions associating investor type and behavior with investment outcomes.

This empirical study uses the Crunchbase dataset to provide a new view into CVC investments, but it does not show significant effects resulting from CVC. CVC investments only show marginal effects on venture outcomes (M&A and IPOs), and no increase in the M&A rate. Longer "exposure" to CVC does not amplify these effects.

Of course, other benefits from CVC investment activities may accrue to CVC parents. A number of them have been discussed previously in the literature, including a "window into new technologies," a novel career path for top performing executives, and a reasonable investment path for otherwise unused cash flow. But the question of cyclicality remains a potent one – the lack of strong, quantitative benefits is consistent with a more opportunistic and trend-driven cyclicality of CVC investing.

In the absence of sustained internal CVC efforts and deep and long-term managerial expertise, we can imagine cyclicality resulting, at least partially, by other managerial motivations, such as the desire to participate in a high-prestige activity (for both the CVC management and for the CVC parent itself). Corporate venturing is a "sexy" activity that confers prestige to the fund managers, even if the compensation may not be changed from other leadership roles in the parent.

Future studies could explore the following areas to better understand these results:

1) A close look at M&A outcomes to examine how often CVC parents acquire their specific CVC portfolio companies may help show in more detail where and how technology and R&D appropriation occurs.

2) A network analysis of investment syndicates exploring CVC and IVC participants and how they cluster together, coupled with outcome data, could also help shed light on selection effects (joining syndicates) and better clarify if CVCs are simply following good investors into positive performing investments.

Appendix – Summary Stats: US vs. ex-US

	CVC funded ex-US (N=8584)	CVC funded US (N=7553)	No CVC funding ex-US (N=22102)	No CVC funding US (N=21287)	Total (N=59526)	p value
funding_total_usd						< 0.001
N-Miss	1271	506	6664	4524	12965	
Mean (SD)	53759603.2 (422598387.6)	62170109.3 (375910851.0)	11835739.1 (94993361.0)	17943869.8 (58267272.9)	28237580.1 (232484491.3)	
Range	287.0 - 20644700000.0	1700.0 - 22212450000.0	903.0 - 7100000000.0	1000.0 - 2295000000.0	287.0 - 22212450000.0	
funding_rounds						< 0.001
Mean (SD)	2.5 (1.9)	3.7 (2.5)	1.7 (1.2)	2.3 (1.8)	2.3 (1.8)	
Range	1.0 - 43.0	1.0 - 28.0	1.0 - 16.0	1.0 - 43.0	1.0 - 43.0	
industry						< 0.001
bio	679 (7.9%)	885 (11.7%)	1220 (5.5%)	1755 (8.2%)	4539 (7.6%)	
other	3299 (38.4%)	1837 (24.3%)	8532 (38.6%)	6640 (31.2%)	20308 (34.1%)	
tech	4606 (53.7%)	4831 (64.0%)	12350 (55.9%)	12892 (60.6%)	34679 (58.3%)	
employee_count						< 0.001
1-10	2149 (25.0%)	1424 (18.9%)	7140 (32.3%)	7833 (36.8%)	18546 (31.2%)	
10000+	37 (0.4%)	37 (0.5%)	56 (0.3%)	87 (0.4%)	217 (0.4%)	
1001-5000	121 (1.4%)	102 (1.4%)	135 (0.6%)	175 (0.8%)	533 (0.9%)	
101-250	477 (5.6%)	728 (9.6%)	797 (3.6%)	810 (3.8%)	2812 (4.7%)	
11-50	2994 (34.9%)	3017 (39.9%)	7400 (33.5%)	7730 (36.3%)	21141 (35.5%)	
251-500	238 (2.8%)	327 (4.3%)	351 (1.6%)	462 (2.2%)	1378 (2.3%)	
5001-10000	52 (0.6%)	31 (0.4%)	65 (0.3%)	90 (0.4%)	238 (0.4%)	
501-1000	224 (2.6%)	192 (2.5%)	345 (1.6%)	401 (1.9%)	1162 (2.0%)	
51-100	807 (9.4%)	1130 (15.0%)	1521 (6.9%)	1918 (9.0%)	5376 (9.0%)	
unknown	1485 (17.3%)	565 (7.5%)	4292 (19.4%)	1781 (8.4%)	8123 (13.6%)	

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Chapter 5: Conclusions

A. Key Findings

By closely examining a large dataset (Crunchbase) it is possible to begin to understand the longitudinal behavior of angel-funded startups for the first time. Although it is commonly thought that angel-funded companies move on to venture funding later in their development, the data instead demonstrates that such angel to VC transitions are quite rare, and in particular are extremely rare in capital intensive industries like biotech. Chapter Two explores this A2VC phenomena, classifies startups by their investor patterns over time, and looks at success rates for these various startup subsets. We find that the funding source and pattern is strongly correlated to venture success, with VC-funded firms having the highest success rates and the purely angel-funded firms with the lowest. Finally, we observe that this A2VC rate appears to be climbing over time, suggesting that perhaps angel investors are becoming better at selecting VC-fundable companies.

Chapter Three explores one possible contributing factor to this remarkably low rate of A2VC transition in the biotech industry. Biotech VCs are developing a new model of operations where they found – but do not select and fund – startups. Dramatically more capital is being made available to the VC-founded biotechs but "scrappy" startup biotechs are being starved of capital pointing to a possible market failure.

If institutional venture investors are starting to found – and not fund – startup biotechs, corporate venture fund may offer an alternative or complementary funding source. Chapter Four explores this alternative to institutional venture capital, but does not succeed in showing that CVC has a positive impact on venture outcomes nor evidence of internalization of R&D/IP through increased M&A activity.

Together, these studies paint a picture of capital allocation to startups that in robust but concentrated, with many angel-funded "scrappy" startups struggling with future funding. If institutional venture investors are avoiding angel-funded firms and turning more to company creation, then a market funding failure may be emerging – a market failure that is strongest in the biotech sector.

B. Contributions to the Literature

This dissertation employs empirical methods, examining real-world data with novel tools and lenses and allowing the data to tell stories that may be initially counterintuitive and unconventional. Management science is performed for several reasons: to ask interesting questions and explore interesting phenomena, to deepen theoretical understandings of how the world works, to provide policy prescriptions, and to inform entrepreneurial practice (Bartunek, Ireland, and Texas 2006). These studies aim to develop and explore rigorous descriptions of these unexpected findings and to follow their implications in several distinct directions.

This thesis contributes to the field in several specific ways. By identifying the low rate of angel to venture transitions, Chapter two explores unexpected phenomena in detail, demonstrating its validity across time, geography, and industry. Some possible explanations are proffered, but fundamental questions are raised by this finding that may prove fruitful to explore in further research. Chapter three

also explores the rapid increase of a related phenomenon in the venture community – the growing role that biotech venture firms play in creating startups internally as opposed to funding external startups. Both chapters challenge conventional wisdom and question if significant market failures result from these behaviors. Chapter four explores in more detail an alternative funding source – corporate venture capital – but ultimately shows a skeptical picture on the value-add of CVC to both portfolio companies and the CVC corporate parent.

These studies have important implications for entrepreneurial practice. If scrappy, angel-funded firms are rarely able to transition to venture funding, particularly in the capital-intensive field of biotechnology, then alternative funding strategies must be developed that do not assume future institutional venture funding. Startup business plans need to reflect this reality more honestly and early/angel investors need to be skeptical if future venture funding following initial angel investment forms a key part of the startup's plan. CEOs of angel-funded startups will need to adjust business plans, goals, and exit strategies to account for these funding realities.

Important policy implications stem from this work as well. Many entrepreneurial incubators, bootcamps, and support services developed at universities and localities and funded by philanthropists posit that coaching new entrepreneurs coupled with modest seed funding should enable a new CEO to develop a pitch that can be rolled out subsequently to the venture community. However, if this path is uncommon and, as VCs do more company formation, the path becomes even more rare, then supporters of the startup community will need to think carefully about the direction they provide and explore alternative growth and funding paths for entrepreneurial ventures.

C. Generalizability

Hellman's study of angel to venture transitions focuses on a small set of firms in British Columbia. This thesis expands significantly upon Hellman's work by using the entire Crunchbase dataset over a 15-year time period (2000-2015). Later data were not used, as there is an expected right-side "exit bias" – newly formed firms will not have had enough time to either potentially make the transition to venture funding or have a successful exit.

The Crunchbase dataset is much sparser in the early years of this study (early 2000s), as Crunchbase began operations in 2007. It was able to build some data from previous years; however, data preceding 2000 are quite thin, posing the risk of significant selection bias.

Over time, the Crunchbase dataset has continued to improve in quality and comprehensiveness (Dalle, Den Besten, and Menon 2017). Repeating this analysis with new data from Crunchbase over the next 5 years would be quite interesting and worthwhile to explore if the dataset continues to improve and to determine whether this affects any of the results shown in this thesis.

This thesis does explore a broad dataset across the entire US while comparing it to the entire ex-US dataset, and the results are similar across both sets. In addition, the US states are grouped into two categories: VC-hub states – where is there is a high concentration of venture investment activity and where many VCs are located (i.e., Massachusetts and California) – and other states with low such activities. This grouping allows for testing of generalizability but also teases out the potential benefits to firms of locating in venture-rich state hubs.

Finally, the analysis is performed across multiple industry groups. There are certainly differences in results depending on the specific industry examined, with biotech and tech showing the strongest differences. This finding leads to further questions about the differences in these industries, including capital intensiveness, risk profile, and product development timelines.

D. Future Research Questions and Directions

This thesis documents a set of novel findings associated with financing startup ventures, looking in particular at angel and venture financing of biomedical ventures. A number of possible future directions for research are identified through the course of this thesis.

Two broad questions arise that cut across chapters in this thesis. First, how good is the quality of the data in Crunchbase, and do we see differences in data quality between angel and VC deals? Secondly, how can we explore the appropriateness of using Crunchbase's data on IPOs and M&As as proxies for entrepreneurial success?

At the level of each key chapter, a number of possible additional research questions and directions can be explored:

Chapter 2 – A2VC

It is clear that a small subset of angel-funded ventures makes the A2VC transition. In this study, however, we do not closely examine the characteristics of these firms that enable such a transition. A closer look at the specific subsets of angels that invest in companies that do make the A2VC transition repeatably might offer important insights into what differentiates these angels from others without such a track record. This is a form of angel to VC syndication, and studying patterns that emerge in these syndicates could be helpful. Similarly, a subset of angels become venture investors, so understanding more about this subset could be enlightening. Finally, we show significant differences in A2VC rates and success rates across different industries, and we have some sense that at least one factor contributing to these differences is capital intensity. A deeper exploration of these industry differences would be interesting – both capital requirements but also other characteristics, including risk profile and product development timelines.

Chapter 3 – Biotech VCs as Company Founders

This study focuses tightly on data from Massachusetts-based biotech startups in two distinct time periods – 2007/2008 and 2017/2018. This study could be expanded geographically (in particular to look at other VC hubs, such as California) as well as in time (but looking at a broader set of time periods). The phenomenon of VC founding companies is clearly at play in the biotech sector, but we have not examined if other industry sectors are seeing similar patterns. It would also be quite interesting to look at venture outcomes at the VC level to see if this novel investment strategy delivers outsized returns.

Chapter 4 – CVC Impact on Venture Outcomes

A close look at M&A outcomes to examine how often CVC parents acquire their specific CVC portfolio companies may help show in more detail where and how technology and R&D appropriation occurs. A network analysis of investment syndicates exploring CVC and IVC participants and how they cluster

together, coupled with outcome data, could also help shed light on selection effects (joining syndicates) and create a better understanding of whether CVCs are simply following good investors into positive performing investments.

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Experience

LabShares Newton, LLC 2019-present
CEO: Developed, funded and currently lead biomedical incubator/shared lab that has been home to over 20 biotech startups.

Siamab Therapeutics, Inc. 2012-2019
President and CEO: Oversaw development of novel cancer immunotherapies. Developed lead program through late pre-clinical studies in ovarian cancer. Negotiated partnership with Boehringer Ingelheim. Raised $20m from 2 pharma companies, family offices, and grants.

Edimer Pharmaceuticals, Cambridge, MA 2009-2012
Senior Director, Business Development and Operations: Led finance, operations, manufacturing, scientific collaborations & relationships in orphan drug company funded by Third Rock Ventures.

Alnylam Pharmaceuticals, Cambridge, MA Director, Strategic Alliances 2008-2009

Biogen Idec, Cambridge, MA 2006-2008
Co-Founder and Head of Business Operations, BI3 - Biogen Idec Innovation Incubator

The Telluride Group, Newton, MA 1995-2004
Founder and President: Built a health care IT company through successful sale to mindSHIFT Technologies, funded by Fidelity Ventures.

Education

Ecole Polytechnique Fédérale de Lausanne, *PhD Candidate* in Business/Finance
Thesis research focusing on financing of healthcare ventures.

Harvard/MIT Division of Health Sciences and Technology (HST), ***Masters of Science***
Coursework at Harvard Medical School included immunology, cancer biology and pharmacology; clinical internship at MGH.

Sloan School of Management, *Masters of Business Administration*

Harvard College, *A.B. Cum Laude*, Philosophy Concentration

Teaching/Academic

Course Director, Harvard/MIT HST 590 PhD seminar series, Spring 2008 – Present
Topics: Biomed Ethics, miniMBA for Biomedical Engineers, Biomedical Innovation in Global Health
Brandeis University, Lecturer in Biotechnology Masters Program, 2010 – present

Current Board Memberships & Community Activities

NWW Committee for Community Living, Human Rights Committee/Board Member 2012-
Harvard Alumni Association, Cambridge, MA, multiple roles 1994-

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