Essays on Entrepreneurial Finance

by

Dan H. Vo
B.A., University of Victoria, 2005
M.A., University of Victoria, 2007

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Supervisory Committee

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Abstract

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In many developed countries angel capital investment is the main source of external financing for high growth early-stage entrepreneurial companies. In spite of its importance, research in the angel capital market is still very limited. This is partly due the fact that data on angel capital investment is rare and unsystematic. This dissertation attempts to learn more about this important but not well-understood angel capital market. In particular, the first essay looks at the relationship between angels and venture capitalists in financing start-up ventures. This essay juxtaposes a complements hypothesis – angel financing is a springboard for venture capital, against a substitutes hypothesis – angels and venture capital are distinct financing methods that ought not to be combined. The result shows that companies that obtain angel financing subsequently obtain less venture capital, and vice versa. On average venture capitalist make larger investments, but this alone cannot explain the substitutes pattern. In addition, this essay reports that companies funded by venture capital perform better than angel backed companies, as measured by successful exits or revenues. Mixing angel and venture capital funding tends to be associated with worse performance. The second essay studies the role of geographic distance between the angel investors and the investee companies on the angel investment performance. This essay conjectures four possible channels that can explain the relationship between distance and the return to angel investment. It shows that distance has a positive relationship with the return to angel investment. Examining the effect of distance across different categories of angel investors, across angel investor's locations, and across company's location, this essay finds evidence that this positive relationship is mainly driven by the "objectivity effect", which suggests that distant investors can evaluate the prospect of a company more objectively than close-by investors, who tend to be more biased in their judgments. The third essay examines why entrepreneurs find it generally hard to find angel investors. This essay modifies the standard search model introduced by Pissarides to explain this phenomenon. In this model, angels hide to

force entrepreneurs to engage in a costly search. The result shows that angel investors adopt the hiding strategy to screen out low-productivity entrepreneurs who would otherwise inundate angels. Interestingly, social surplus is often increased when angels hide, though in some circumstances surplus may fall.

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Chapter 1: Introduction

1.1 Introduction

One of the most challenging tasks for entrepreneurs in starting and growing a new high-growth ventures is attracting external financing. The risky nature of investing in early-stage ventures, involving no tangible assets and uncertain prospects, discourages potential investors and banks. To survive and to grow, early-stage ventures must typically rely on two main specialists sources of external financing: angel investors and venture capitalists.

Angel investors are wealthy individuals who invest their own wealth in early-stage ventures that are owned by people other than their own family and friends. Angel investors, so-called “angels”, by providing financing and sometime expertise help bridge the gap between an entrepreneur’s intellectual assets and an entrepreneur’s commercially viable business.

In the past decades, angel capital investment has been recognized as the primary source of external financing to high growth early-stage ventures in many countries. Indeed, it has been documented that angels supply more capital to early-stage ventures than do venture capitalists. A recent OECD (2011) report estimates that the total angel capital market is approximately the same size as the venture capital market in the United States, Canada and some European countries. Wiltbank (2005a, 2005b) finds that angel capital is the main driver behind economic growth and job creation in the United States, and possibly else in world.

In spite of its importance, research on angel capital investment is quite limited due to the lack of data. This dissertation contributes to the literature by developing and analyzing a detailed data set assembled from the British Columbia Venture Capital Program. This data set provides a unique opportunity to test theories about the angel capital market. In particular, with this data I’m able to provide answers to the following two questions:

1. How do angels and venture capitalists interact in the context of financing start-up companies?

2. What is the role of geographic distance in determining angel investment performance?

In addition, this dissertation, attempts to answer a third question:

3. Why is it so challenging for start-up ventures to find angel investors?

To answer this question a search-theoretic theoretical model is developed.

1.2 Overview of the Dissertation Chapters

Chapter 2 empirically examines the relationship between angel investors and venture capitalists in financing early-stage entrepreneurial ventures. Specifically, it analyzes how companies dynamically choose between these alternative investor types, and how these choices affect company performance. This chapter juxtaposes a complements hypothesis, where angel financing is a springboard for venture capital, against a substitutes hypothesis, where angels and venture capital are distinct financing methods that ought not to be combined. Using a unique detailed dataset of start-ups in British Columbia, Canada, this chapter shows that companies that obtain angel financing subsequently obtain less venture capital, and vice versa. This substitutes pattern is more pronounced for companies funded by less experienced angels. As for performance, This chapter reports that on average companies funded by venture capital do better than angel backed companies, as measured by revenues or successful exits, and venture capitalists make larger investments. Mixing angel and venture capital funding tends to be associated with worse performance. Overall the evidence favors the substitutes hypothesis.

Chapter 3 empirically studies the role of geographic distance on angel investment performance. This chapter hypothesizes four possible channels through which distance may play a role in determining angel investment performance. The information effect and objectivity effect occur at the selection stage. The advising effect and network effect occur at the value-added stage. Using the British Columbia Venture Capital Program data, this chapter shows that the return to angel investment is positively related to distance. Further examining the relationship of distance across different categories of angel investors, across company's locations, and across angel investor's location, reveals that the returns to distance are largest for the smallest and least experienced angel investors and for companies located in a center. These findings suggest that the positive relationship between distance and return is dominantly driven by the objectivity effect, where local angel investors who might be unduly swayed by an enthusiastic entrepreneur.

Chapter 4 adopts of a search framework introduced by Pissarides (2000) that is commonly used in the labor literature to explain the why it is generally hard for entrepreneurs to find angel investors. Angel's hiding behaviour forces entrepreneurs to engage in a costly search. In the model, high-productivity entrepreneurs have a greater value of search than low-productivity entrepreneurs. Therefore, angel investors adopt the hiding strategy to screen out low-productivity entrepreneurs who would otherwise inundate angels. Interestingly, social surplus is often increased when angels hide, though in some circumstances surplus may fall. "Hide and seek search" stands in contrast to the traditional search theory, where the search friction represents inherent physical and informational impediments to trade, as well as directed search, where inherent coordination problems generate impediments to matches.

Chapter 2: Angels and Venture Capitalists: Complements or Substitutes

2.1 Introduction

Much of the policy debate and academic literature on entrepreneurial finance focuses on venture capital. But angel investors are another important source of funding for start-ups. An OECD report from 2011 notes that "While venture capital tends to attract the bulk of the attention from policy makers, the primary source of external seed and early-stage equity financing in many countries is angel financing not venture capital" (OECD 2011, p.10). This same report estimates that the total angel market is approximately the same size as the venture capital market, an estimate in line with earlier studies (e.g. Mason and Harrison, 2002a, Sohl, 2003).

In this paper we ask whether angel investors and venture capitalists (VCs henceforth) should be thought of as complements or substitutes. We address two main aspects of the relationship between these two types of financiers. First, in the context of dynamic investment patterns, we ask whether companies that obtain angel funding are more or less likely to subsequently obtain VC funding, and vice versa. Second, we consider the relationship between investor types and outcomes, and ask whether companies that combine angel and VC funding outperform companies that obtain funding from only one source.

What should we expect about the dynamics of angel and VC investments? Under the substitutes hypothesis, angels and VCs constitute alternative investment models that do not mix well together. Once a start-up has chosen one type of investor, it is less likely to switch to the other type. Under the complements hypothesis, however, each type of investor offers a different piece of the puzzle. Obtaining one type of financing actually increases the start-ups' chances of obtaining the other. For instance, one may conjecture that angel financing is a springboard to obtaining VC.[1]

[1] Famous examples of start-ups that started with angel funding and proceeded to VC include Facebook and Google.

What performance implications should we expect of using different investor combinations? Under the complements hypothesis start-ups have supermodular production functions, where the use of one input becomes more valuable in the presence of the other. By contrast, the substitutes hypothesis argues that the production function is submodular, so that the use of one input becomes less valuable in the presence of the other. The difference between complements and substitutes can be viewed as a horse race between the benefits of diversity versus the benefits of specialization [2].

This paper presents new empirical evidence that allows us to examine these alternative hypotheses. By far the biggest obstacle to researching angel investments has been access to credible and systematic data. We collect data from the Venture Capital Program in British Columbia, Canada (henceforth the VCP). The regulatory filings under the VCP offer a unique opportunity to obtain systematic and detailed data on angel as well as VC investments. While venture capital programs exist in many part of the world, British Columbia is one of the few places where the tax credits are made available not only to VC firms but also to angel investors (Sandler, 2004). Central to the development of the database is a requirement to file documents that list all the companies' shareholders over time, which allows us to construct detailed and comprehensive financing histories of start-ups. Our data includes 469 starts-up that were first funded over the period 1995-2009.

Our data also posits challenges. For example, there is no universally accepted definition for what exactly distinguishes angels from VCs.[3] We adopt the following approach: an angel investor invests his/her own family's wealth, whereas a VC invests on behalf of other fund providers.[4] This definition is based on a fundamental economic distinction between direct versus intermediated financing. From a theoretical point of view, one would expect that investors

[2] Note the two interpretations of the substitutes versus complements relationship described above are not necessarily independent. For example, if we found complementarity between angels and VCs in terms of performance (i.e. a supermodular production function), then anticipating such supermodularity, investors will avoid to interact with each other resulting in the substitutes dynamic investment pattern.

[3] This is further discussed also OECD (2011) and Goldfarb, Hoberg, Kirsch, and Triantis (2012)

[4] In the data we still have to deal with several borderline cases, most notably so-called "angel funds" where several individuals pool their investment funds. One of them typically takes a leadership role in terms of screening out projects, and hence acts a little bit like an intermediary for the others. Empirically it is difficult to distinguish between active and passive investors, but the fact that all these individuals invest their own money suggests they are angels.

investing their own money face different incentives and constraints than investors who are intermediaries that act on behalf of others.[5] In addition to angel investors and VCs, we also identify a variety of other investors, including corporations, financial institutions, not to mention founders and their families.

We analyze financing patterns by utilizing the dynamic structure of data, asking specifically how prior investments relate to subsequent investment choices. Our regressions contain a rich set of controls, including company characteristics and a variety of time clocks. We find strong evidence for dynamic consistency within investor types. A company that already obtained funding from one particular type of investor is likely to raise more funding from that same type. We also find a clear substitutes pattern between angels and VCs. Companies that have obtained VC funding are less likely to subsequently obtain angel funding. Maybe more surprisingly, we also find that companies that have obtained angel funding are less likely to then obtain VC funding. These findings apply equally to the probability of obtaining funding as well as the amounts raised in case of funding. The substitutes pattern continues to hold in a model with company fixed effects that control for time-invariant unobserved heterogeneity. Differences in investment amounts between angels and VCs also cannot explain away the substitutes pattern.

A unique strength of our data is that it allows us to distinguish between different types of angels. We separate angels into less versus more committed angels based on whether they invest in a single or in multiple companies. We find that the substitute pattern is more pronounced for the less committed angels. Specifically, our results suggest that companies backed by one-company angels experience significantly lower chances of obtaining VC funding. One possible interpretation of this result is that VCs tend to avoid mixing with less committed angels.

To analyze performance we consider several outcome measures. The most common measure of success in the VC literature is whether a company exits, either through an acquisition or an IPO (see Phalippou and Gottschalg, 2009). We also consider the likelihood of death, i.e. going out of business. Another indirect measure of success can be whether a company raises a particularly large financing round. We examine the likelihood of raising an investment round of at least

[5] See also Diamond (1984) and Axelson, Strömberg and Weisbach (2009).

$10M. For a subset of our sample companies we are also able to observe revenues and employment.

We first examine the direct relationship between investor type and company performance. In the absence of an instrumental variable we are cautious not to impose a causal interpretation on any of the effects. We find that obtaining more venture capital is associated with better performance outcomes, a result that is consistent with much of the prior literature. Interestingly, the same is typically not true for investments from angel or other investors. Moreover, companies funded by less committed angel investors tend to have a somewhat lower performance than those funded by more committed angels.

We then augment the model to also include interaction effects. Again we caution that the coefficients on the interaction terms should not be given a causal interpretation, as there can be unobserved company characteristics that determine both a company's investor choices, as well as its subsequent performance.[6] All the estimated coefficients on the interaction terms indicate a negative relationship, although only some are statistically significant. This provides suggestive but not conclusive evidence for a submodular production function, where mixing angel and VC funding is associated with lower performance, compared to using either only-angel or only-VC funding. Finally, we also find some evidence that the negative interaction effects between angels and VCs are more pronounced for less committed angels.

Overall our evidence favors the substitutes over the complements hypothesis. This is true in terms of the dynamic investment patterns, and it also seems to apply to the relationship between investor choices and company outcomes.

The academic literature on angel financing remains underdeveloped. The paper closest to our is Goldfarb et al. (2012), who make use of a unique dataset from a bankrupt law firm that contained term sheets from client firms, some of which obtained angel and/or VC financing. They show that VCs obtain more aggressive control rights than angel investors. This finding is consistent with what we know about VCs (e.g. Kaplan and Strömberg, 2003) and other research on angel investors (Van Osnabrugge and Robinson (2000) and Wong (2010)). Most interesting, Goldfarb

[6] See Athey and Stern (1998) and Cassiman and Veuglers (2006) for further discussion on this.

et al. (2012) find a negative effect of mixing angel and VC funding, similar to the results found in this paper. Their analysis suggests that this result is driven by split control rights, where neither angels nor VCs have firm control over the companies' board of directors. Our analysis augments the work of Goldfarb et al. (2012) in several important ways. For each company they only have a single snapshot of one financing round, whereas we have an entire financing history. As a result, Goldfarb et al. mainly focus on syndicated investment where angels and VCs invest in the same round. Our data allows us to consider richer dynamic relationships. Interestingly, our data also suggests that syndicated angel-VC investments are somewhat rare. In our sample only 7% of all financing rounds involve syndication between angels and VCs.

Kerr et al. (2013) examine data from two angel groups that keep track of which companies present in front of the group, and which companies actually get funded. Using a regression discontinuity approach, they find evidence that obtaining angel funding affects the companies' growth and survival rates. While they have more detailed evidence on the investment decisions of angel investors, they can only look at a specific part of the angel community, namely those associated with angel networks. They also do not consider the interrelationships between angels and VCs.

Two papers provide some theoretical foundations for comparing angels and VCs. Chemmanur and Chen (2006) assume that VCs add value but angels don't. Their model explains why entrepreneurs sometimes first obtain angel financing before switching to VC. By contrast, Schwienbacher (2009) assumes that both angels and VCs can add value, but that only VCs have enough money to refinance a deal. Under his set-up angels endogenously provide more value-adding effort, because of the need to attract outside capital at the later stage.

The literature on VCs is much larger than that on angel investors. Most relevant to this paper is the part of the literature that compares different types of VCs, such as corporate VCs, bank VCs and also government-supported VCs. Da Rin, Hellmann and Puri (2013) provide a comprehensive survey of that literature.

The remainder of this paper is structured as follows. Section 2 discusses data sources and variable definitions. Section 3 examines the dynamic financing patterns across different investor types. Section 4 examines the relationship between financing patterns and company performance. It is followed by a brief conclusion.

2.2 Data and Variables

2.2.1 The BC Venture Capital Program

The BC provincial government administers a Venture Capital Program (henceforth, the VCP) that is based on a 30% tax credit for BC investors investing in BC entrepreneurial companies. The VCP was first established in 1985 under the Small Business Venture Capital Act of British Columbia. By the end of our sample period in 2009, the VCP program had four segments. The first two segments consist of what we will henceforth call *retail funds*. Retail funds have obtained a special license to raise money from the general public. Individual investors receive a 30% credit for investments into retail funds, up to some limit ($10K in 2009). The main eligibility criterion is that the investors are BC residents. The retail funds then have an obligation to invest these funds within a certain time. There were two types of retail funds in BC. The first was a part of the labour-sponsored venture capital program which involved sharing of the tax credit between the federal and provincial governments. The second was a very similarly structured program that was purely funded by the provincial government.

The third and fourth segments of the VCP primarily target angel investors. The third segment of the VCP program consists of tax credits for investments in funds which do not have a license to gather funds from the general public. These funds are called *VCCs*, for Venture Capital Corporations, as the program requires them to be structured as corporations.[7] VCCs can only raise money from BC-based "eligible investors". For individual investors this means they need to satisfy some qualified investor criterion (based on wealth, earnings, or "sophistication"), or else demonstrate to have a prior acquaintance with the VCC fund managers (either based on a family relationship or professional contacts.)

The fourth segment of the program was introduced in 2003 and is called the EBC program. It consists of tax credits for direct investments of BC-based eligible investors into entrepreneurial companies called EBCs (Eligible Business Corporations). This program is administratively much

[7] Readers familiar with the VCP may note that the provincially funded retail funds are also structured as VCCs, albeit with the additional rights to raising funds from retail investors.

simpler for angels than the VCC program since it does not require them to set up an investment vehicle. Indeed, the EBC program was intended to reach out to a wider set of angels, including those for whom the volume of tax credits was too small to warrant the effort and costs of setting up a VCC. Eligible investors, including angels, can simply claim the 30% tax credit on the basis of an investment in an EBC. Under the VCC and EBC segments of the VCP, individual investors can claim tax credits for investments up to $200K.

There are several requirements on the companies under the VCP. In order to qualify to receive investments under any of the segments of the VCP, companies must be BC-based businesses that (together with affiliated companies) at the moment of registration have no more than 100 employees, pay at least 75% of the wages and salaries to BC employees, and operate in an eligible industry.[8]

2.2.2 Data Sources

The data for this paper comes from a variety of sources. Our primary source is the Government of British Columbia, who administers the VCP program described above. What makes the VCP unique, and useful for our analysis, is that it applies to investments by both angel investors and venture capitalists. Sandler (2004) shows that the bulk of the North-American public policy initiatives target formal venture capital, rather than the angel segment of the market.

Our dataset contains detailed investment data related to the tax credits claimed under the program. The BC Government also requests detailed company information at the moment the companies register under the program. During registration companies provide data on their balance sheets, profit-and-loss accounts, and the number of employees at the moment of registration. For about half of the companies we also have their business plans. In many cases companies continue to file these documents on an annual basis thereafter. For example, companies who successfully attract risk capital after registering for the program are required to submit so-called annual returns that contain some financial information (mainly revenues and assets), as well as employment figures.

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[8] Further information on the program can be found in Hellmann and Schure (2010), Lerner et al. (2012), and on the provincial government's website at http://www.jti.gov.bc.ca/ICP/VCP/.

For a substantial subset of our companies we also have share registries. These documents are particularly important for our analysis, since they contain the complete history of companies' shareholders, dating back to the date of incorporation, and listing the precise dates of when shareholders obtained their shares. As a consequence our data contains not only the investments made with tax-credits, but also those made without tax-credits.

We augmented the VCP data using several additional data sources. First, we consulted several sources to classify investors into types. Investors do not only include angels and venture capitalists, but also other financial parties, corporations, and smaller groups such as universities, charitable organizations, etc. Secondly, we gathered additional data about the companies in the VCP dataset. We are interested in how companies evolve and perform after their initial registration with the program. The BC Government data includes some information due to the fact that the VCP requires companies to file an annual report. However, we collected performance indicators other than those provided by the BC Government. The additional data sources we consulted are: the BC company registry; the (Canadian) Federal company registry ("Corporations Canada"); Capital IQ; ThomsonOne (VentureXpert, SDC Global New Issues and SDC Mergers and Acquisitions); Bureau Van Dijk (i.e. a data provider that collects private company data – for Canada, the main source of the Bureau Van Dijk data comes from Dunn and Bradstreet); SEDAR, which contains the record of filings with the Canadian Securities Administrators of public companies and investment funds; and the Internet (using mostly Google searches and an internet archive called the Wayback Machine (http://archive.org/web).

2.2.3 The Company Dataset

We have information of companies that registered under the VCP during the period of Jan 1995 to March 2009. Our dataset consists of 469 companies, although we are not always observe all relevant variables for all of them.

One concern is whether our company dataset represents a random selection of BC high-tech startup companies. This question is very difficult to answer. Even we could pinpoint the companies outside the VCP we would not have the data to assess whether their financiers relate to these companies and one another in the same fashion as the VCP companies in our dataset.

What we can do is to compare our dataset to other datasets of high-tech start-ups, such as the Venture Economics and the “Brobeck company database”[9]. Let us turn to this next.

With respect to company’s age, at the time of their first financing the average company in our sample is 2.4 years old. We then observe companies’ financing history for an average of 3.8 years after this moment, so they are on average 6.2 years old by the time of the last financing round we observe. We then continue to observe the companies until they experience an exit (IPO or acquisition), or fail, or reach the end of the sample period while still alive. The company is on average 10.2 years old by the time we observe them last.[10] By contrast, the average age of the Brobeck companies and those in Venture Economics are 1.8 years and 3.1 years, respectively, as reported in Goldfard et. al. 2012. This suggests that our companies are similar in term of age at first financing.

Turning to the industries of our companies, we manually match each company’s business activity to an industry classification for innovative companies that is loosely based on NAICS codes. For most of the companies in our sample, we obtain their business activities from the business plans and registration applications. We use the internet search for the remaining companies. As shown in Panel A of Table 1, most of the VCP companies are active in the software industry or hi-tech manufacturing. Together these two industries account for almost half of the companies in our sample. When taken together, high-tech companies account for almost 78% of the companies in our data including 12% of the companies that are classified as life sciences. The other 22% of the companies are mainly focusing on tourism or non-high-tech manufacturing, mainly for exports. These industries are eligible because they are also deemed to further the main objective of the VCP program, namely to “enhance and diversify the BC economy”. The portion of high-tech and life sciences companies in our sample is quite similar to Venture Economics’ companies and Brobeck’s companies. As reported by Goldfarb et. al. 2012, 82% of companies in the Venture

[9] Venture Economics (Venture Xpert) is a self-reported dataset managed by Thomson Reuters. It is one of the two primary venture captain databases (VentureOne database is the other) commonly used by researchers to study venture capital financings. The Brobeck company database consists of the electronic records of companies and their investors of the bankrupt San Francisco law firm Brobeck, Phleger & Harrison. For more detail information on the Brobeck company database, see Goldfard et. al. 2012.

[10] We are not always able to observe all financing rounds up to exit, as companies may stop reporting them after a while. For the investment analysis we stop our sample at the time of the last observed financing round. For the performance analysis, however, we use the entire sample until the time of exit.

Economics database is considered as high-tech companies. The portion of high-tech companies among Brobeck's companies is 82%.

We follow companies up to the moment they exit, or the end of 2012, whichever moment comes earlier. We learn about their exit status of through a number of data sources. We use SDC Mergers and Acquisitions, SEDAR, CapitalIQ, LexisNexis and internet searches to check whether companies were involved in IPOs or acquisitions. We use the BC and Canadian corporate registries to check for the status of the remaining companies. The corporate registries are quite reliable as companies are required to submit documentation annually. As of December 2012, 64% of the companies in our dataset are still active; 13% of the companies have exited through either an IPO or an acquisition;[11] and the remaining 23% have failed. Clearly, the active companies is over-representative in our sample, which is due to the fact that we include the most recent registered companies under the VCP program at time that the data was provided to us in March 2009. The tradeoff between greater sample size and more precision estimate on the financing sequence and better representative sample in term of exit is inevitable. We however find that the former outweighs the latter at least for the purpose of this study.

With respect to deal size, our companies receive on average 1.5 Million CAD in a financing round. This is fairly small in compared to the average deal size in a financing round for Brobeck's sample and Venture Economics' sample, which are $6.14 Million and $7.15 Million respectively (Goldfarb et. al. 2012). This suggests that our companies are relatively smaller on average. This is not a surprise to us as the Canadian economy is also about 10 times smaller than the US economy.

For the majority of the companies in our sample, we also observe their location through the VCP data (from either the business plans, the registration application, and/or annual filings). We use internet searches to find the location of the remaining companies. As shown in Panel A of Table 1, our companies are concentrated in and around Vancouver – 73% of them are located in the

[11] We also use another measure of success as an alternative to IPO or acquisition. We constructed the variable "major deal", indicating whether a company receives any major round exceeding ten millions CAD during the time we observe it. As shown in Panel A of Table 1, about 8% of our sample companies ever secured a major deal.

Greater Vancouver Regional District (GVRD).[12] The two smaller hubs for innovative activities are Victoria (the Capital Region District of BC), and, in the East of BC, the adjacent areas of the Okanagan and the Thompson River Valley.

We also collect data on company's revenue and number of employees. These figures are available at registration and often also in the company's annual filings, which usually include annual reports. Collecting data from financial statements involved a labour-intensive manual process of scanning and transcribing paper documents into electronic format, and creating some standardization. We report annual revenues for all quarters for which a financial statement applies.[13] Financial statements are typically not available for all years. We obtain revenues for 5424 company-quarters, representing 334 distinct companies. Collecting employment is even more difficult, because they are not reported in financial statements. We therefore rely on administrative filings, hand-collected survey data and BVD (see Hellmann and Schure (2009) for details). We obtain employment data for 3414 company-quarters, representing 275 distinct companies.[14]

2.2.4 The Investor Dataset

Central to our main hypothesis is the classification of investors into distinct types. In total, we observe 13,101 investment transactions, made by 7,603 unique investors in 469 companies. We adopted a two-step approach to classify this population of investors. First, we separated the investors into two groups: humans and vehicles. Human investors are identified by their first and last name. "Vehicle investors" are the remaining ones. To ensure that no human investor is wrongly classified as vehicle investor, we checked on all vehicle investors to see whether there was any corporate designation such as "Ltd.", "Corp.", etc. in their name.

In the second stage, we performed several name-based matches with other data sources to classify the human and vehicle investors into several categories. With respect to the human

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[12] For simplicity we also include in our GVRD definition nine companies that were located in the "Lower Mainland", which is the valley extending inland from Vancouver.

[13] For example, if the financial year starts in July, the first two quarters use the annual revenues from the previous financial year, and the last two quarter use the annual revenues from the following financial year. If the financial year starts within a quarter, we always go to the closest date.

[14] Note that our regression analysis will use lagged dependent variables. This requires consecutive years of revenues and employees, further reducing our sample sizes.

investors, it is important to distinguish angels from company founders, their families, and key employees. To do this, we matched the human investors in the share registry with the list of founders identified in the company's business plan, its annual returns, and other available documents and websites. We also identified non-founding managers and other key employees using the above sources. We furthermore assumed investors are key employees if we observe they acquire shares at a deeply discounted price (10% or less of the maximum share price other investors pay in the same round). Finally we score investors as family members of founders if they invest in the same company and share the same last name as founders. Our method cannot identify those family relationships where family members have different last names. Moreover, our methodology does not allow us to identify founders' friends, as there is no objective criterion for separating those out from angel investors. By the end of the procedure we were able to separate human investors into "angel investors" on the one hand, and founders, family and key employees (henceforth "founders") on the other. Note, however, that we only worked with the share purchases of "founders" made at "regular value" – that is we removed from our data all share purchases at deeply discounted values.

For part of the analysis we further subdivide the angel investor category into two types, distinguishing between those angels who throughout our entire database invest in only one company (although possibly over multiple rounds) versus those who invest in more than one company. We call them "Angel Single" and Angel Multiple" respectively. Investing only once suggests that an individual has limited interest in angel investing *per se*, and may have made the one investment because of a personal connection or other idiosyncratic reasons. However, investing more than once suggests that the individual is somewhat more committed to being an angel investor.

There are over 2,200 vehicle investors in our dataset. We first matched our list of vehicles with the list of Venture Capital Corporations (VCCs) described in Section 2.1. We then separated out VC funds. We first identify an investor as a VC using name-based matching with Capital IQ and ThomsonOne (VentureXpert). Beyond that we classify an investor as a VC if a web search reveals that (a) they declare themselves to be a VC firm, or (b) the fund is managed by a team of investment professionals. We identified a total of 54 VC firms in our dataset. Some of our analysis further subdivides VCs into "Private VCs" and "Government VCs". Following Brander, Du and Hellmann (2013), we include in the Government VCs category not only those VC firms that are directly owned by the government, but also those that directly benefit from government support, most notably all of the retail VCs described in section 2.1.

Some angel investors use vehicles for investments. All of the non-retail VCCs in the VCP program are owned by angel investors, so we classify them as such. In addition we identify several corporations and trusts that clearly bear the names of individuals or families. We search the BC and Federal company registries and internet searches to verify that names represent individuals and not operational entities, adopting a conservative approach, only declaring them as angel if we can positively identify them as such. This approach emphasizes the correct identification of angel investors. We are unlikely to misclassify financial or corporate entities as angel vehicles, although we are likely to misclassify some angel vehicles as financial or corporate entities. The remaining vehicles are either classified as financial or corporate investors. The category of financial investors includes financial institutions that are not VCs (e.g., banks), as well as an assortment of investment vehicles (e.g., real estate funds, pension funds). The category of corporate investors spans a wide range of corporations, including manufacturing and professional service firms.

In order to careful examine investment dynamics we structure our data as a quarterly panel. Within a quarter we aggregate all investment amounts into a single round. However, in practice companies sometimes raise a round over a span of time that either crosses two quarter boundaries, or that exceeds the length of a quarter. We adopt the following pragmatic rules regarding financing rounds and the timing of these rounds. A series of investments is considered to be a single round in the case where an investment takes place within ninety days of a previous investment. The date of the round is then the quarter in which the first investment within the sequence took place.

Panels B of Table 1 provide some descriptive statistics concerning investment round and investor types. The first column of Panel B reveals that a financing round took place in 30% of the company-quarters in our data. This implies that our companies raise money during the time we observe them slightly more often than once a year. Moreover, angel financing seems to be the most common source of financing for the companies in sample. Angels were active during 21%

of all company-quarters, as opposed to 10% for VCs and other investors. The second column shows average round amounts, conditional on observing an investment in a given quarter. The average VC investment round is much larger ($1.75M) than the average angel investment round ($256K) or the average investment from other investors ($192K).This is consistent with the general belief that venture capitalist tends to invest in larger deal than angel investors. Panels C of Table 1 provides further descriptive statistics that focus on the cumulative amount of funding, as measured at the time of the last company round. 85% of our sample companies obtain funding at least some funding from angels, 38% from VCs, and 56% from other investors. However, companies obtain more the six times as much funding from VCs than from angel investors.

2.3 Dynamic Funding Patterns

2.3.1 Preliminary Considerations

In this section we examine the dynamic funding patterns of entrepreneurial companies. Our main focus is how past investor choices affect companies' current investor choice. This question requires us to start our analysis at the first funding round, and then follow companies forward in time. As a preliminary step it is therefore useful to briefly discuss the determinants of the initial choice of investor type.

Table 2 reports the results from OLS regressions about the initial choice of investor type. The dependent variable is the amount of funding received from angel investors (column 1), VCs (column 2) and other investors (column 3).[15] Table 2 shows that the coefficients for company age at the time of first funding are statistically insignificant in columns 1-3. In terms of geographic location, we find that companies located in the rest of BC obtain less VC funding. Most interesting, there appears to be significant industry specializations, especially between angels and VCs. The omitted category is software. Relative to that, angels are found to be more active in Cleantech, High-tech Manufacturing and the "Other industries" category (which includes a wide variety of industries, including agriculture, forestry, fishing, mining, as well as an assortment of other low technology industries). VCs are more likely to invest in Biotech, but less likely to invest in Cleantech, Tourism and the "Other industries" category. Not shown in

[15] In Table 1 we report investment amounts in million Canadian dollars. Starting with Table 2 all amounts variables are based on the natural logarithm of one cent plus the investment amount in Canadian dollars. The addition of one cent allows us keep in the data all quarters where no invest round occurred.

Table 2 are calendar time fixed effects, namely a complete set of dummies for each quarter within the sample period. Columns 1-3 of Table 2 focus on the initial funding across investor types. Columns 4-6 repeat the same regression using the final amount of funding received across the three types. The results are fairly similar, although several coefficients that were insignificant in columns 1-3 are now significant in columns 4-6.

2.3.2 Empirical Specification

We now turn to the dynamics of investor choices. We consider a quarterly panel where we follow our sample companies from their first to their last investment. Our main regressions model, used in Table 3, is as follows:

$$J_{kt} = \alpha + \beta_k \, I_{k,t-1} + \beta_c \, X_c + \beta_{ct} \, X_{ct} + \eta_t + \varepsilon_{ct}$$

The dependent variable is J_{kt}, which is the amount of funding that a company obtains from investor type k in period t. Columns 1-3 of Table 3 consider angel investors, VCs and other investors. Column 4 also considers the total amount of funding from any of these investor types.

The most important independent variables are $I_{k,t-1}$, which measure the cumulative amount of funding that a company received from investors of type k, up to time t-1. Note that throughout the paper, we call the amount of funding received in quarter t the “current” amount, and the cumulative amount of funding received up to quarter t-1 the “prior” amount.

In terms of additional controls, X_c is the set of variables that measure all time-invariant company characteristics, namely company age at the time of the first round, industry or location. We report those controls in Table 3, but for brevity will omit them in all subsequent Tables.

X_{ct} is a set of variables that measure all time-variant company characteristics. These include the time since the first round (measured non-parametrically with a complete set of dummies for each quarter, starting the counter with the quarter when the first round occurs), and the time since the last round (measured non-parametrically with a complete set of dummies for each quarter, restarting the counter every time that new round occurs). This very detailed set of non-parametric controls is meant to capture independent time-varying factors, allowing us to focus specifically on the relationships between prior and current funding choices.[16] All our regression models use these controls, but for brevity's sake they remain unreported.

η_t is a set of calendar time fixed effect (measured non-parametrically with a complete set of dummies for each calendar quarter), which controls for any seasonal effects, any business cycles effects, or indeed any other calendar time effects. All our regression models use these controls, but for brevity's sake they remain unreported.

ε_{ct} is the standard error term. Throughout the paper we use robust standard errors (which in a panel model is the same as clustering by company). We only use OLS panel regressions, but not any non-linear models such as Probit of Logit regressions. This is because the large number of fixed effects in our specifications creates an incidental parameter problem (see Angrist and Pischke, 2009). Note also that our regression model does not consist of one single equation, but of a collection of k equations. At the highest level of aggregation we can consider the case of k=3, comparing angels, venture capitalists and other investors. Below we also consider alternative specifications with higher values of k, that allow for the disaggregation of investor categories.

2.3.3 Results from the Base Model

Table 3 shows the results from the estimation of our base model. The most important results concern the relationships between investor types. We first note that the coefficients on the main diagonal, i.e. the effect of prior financing by type k on current financing by type k, is always positive and strongly significant at the 1% level. This suggests strong consistency over time, where a company that already received funding from one type of investor is likely to receive further funding from that same investor type.

Next we note strong substitutes effects between angels and VCs. If a company has received prior VC funding, it raises significantly less angel funding, and vice-versa. The result that companies with more VC funding receiving less angel funding is probably not very surprising. VCs have deep pockets, so that adding angel money to VC-backed companies may not be so important. However, the results that more angel funding leads to less VC funding is far from obvious, and

[16] Note that our specification implicitly takes care of company age, since we control for both the age at the time of first round, and a clock for time since the first round. Using a clock for company age, instead of a clock for the time since the first round, yields very similar results.

suggests a substitutes, not a complements relationship. This is an important result because it would contradict the conventional wisdom that as companies grow through their development stages, they will receive funding from angels and then from venture capitalists. This result instead suggests that having angel financing will reduce the likelihood of getting VC financing. In other words, once a company chooses to receive angel financing, it is more likely to stay on the angel financing path.

Below we will delve deeper into the possible reasons for this effect. It is also interesting to note that the negative coefficient for prior VC amounts on current angel amounts (-0.0843) is more than twice as large as the negative coefficient for prior angel amounts on current VC amounts (-0.0378). This is an intuitive finding, suggesting that the negative substitutes effect from VCs to angels is stronger than the negative substitutes effect from angels to VCs.

Table 3 also shows that obtaining funding from other investors does not seem to significantly affect angel or VC funding. However, we do find a negative effect of VC funding on subsequent funding from other investors, which is again consistent with the notion that VCs have deep pockets. Column 4 provides further evidence for such a ‘deep pocket’ effect. Looking at the total amount of funding (aggregated over the three types), we find that prior VC funding is associated with more subsequent funding, whereas the effects of prior funding from angels or other investors is statistically insignificant. Finally, note that the company control variables behave broadly similar to our findings from Table 2.

The analysis of Table 3 considers investment amounts for all quarters. This includes quarters where a financing round occurs, as well as quarters where no financing round occurs. Table 4 provides a decomposition of the effects from Table 3, where we distinguish between the probability of having a financing round, and the amount of funding conditional on having a financing round. Panel A of Table 4 estimates the probability of obtaining any funding from investor type k in period t, as measured by a set of dummy variables for each type. Panel B of Table 4 estimates the amount of funding from investor type k in period t, conditional on observing some investment in period t. The sample in Panel A (6815 company-quarter observations) represents the set of potential financing rounds, whereas the sample in Panel B

(1719 company-quarter observations) represents the set of realized financing rounds. The independent variables are the same as in Table 3.

Table 4 shows that the two central findings from Table 3 apply equally to the probability of obtaining funding, as well as the amount of funding conditional on obtaining funding. Specifically, we find that the coefficients on the main diagonal all remain positive and statistically highly significant in both specifications. Moreover, the substitutes effects between angels and VCs also continue to hold in both specifications. This suggests that having prior angel financing predicts both a lower probability of obtaining VC, and a lower amount of VC in case of funding; same for the effect of VC on angels.

2.3.4 Company Fixed Effects

We may ask whether the results from Table 3 and 4 are driven by unobserved heterogeneity. Should we think of the substitutes effect as arising from investor characteristics, such as an incompatibility of investment styles, as discussed in the introduction? Or does the substitutes effect arise from unobserved company characteristics, where certain types of companies lend themselves to only one type of financing. One way to address this endogeneity problem is to use company fixed effects, which control for all time-invariant unobserved company characteristics.[17]

Table 5 reports the results from re-estimating the models from Table 3 with company fixed effects. Our first important finding is that the strong positive coefficients on the main diagonal disappear. The coefficients for angels and VCs are insignificant, the coefficient for other investors is even negative. This suggests that unobserved company characteristics account for the strong correlation between prior and subsequent funding within the same investor type. Put differently, company characteristics can explain why companies continue to obtain angel financing if they already have some prior angel financing; same for venture capital. In the case of other investors, it even suggests that once a company has obtained such funding it is less likely to obtain additional such funding.

[17] Another possible approach for addressing endogeneity problem is to look at instrumental variable specifications that try to also control for potential time-varying unobserved heterogeneity. We plan to address this in future research.

Our second important finding is that unobserved company heterogeneity does not seem to account for the substitutes effects between angels and VCs. Both substitutes effects continue to be statistically significant. The effect of prior angel financing on subsequent VC funding has a slightly lower P value of 7.1%. However, the point coefficient actually increases in the fixed effect regression, suggesting that the loss of statistical significance is attributable to an increase in standard errors, something that is quite common in fixed effect regressions.

2.3.5 Accounting for Different Investment Sizes

A natural question to ask is whether the substitutes patterns identified so far can be explained by different investment requirements. We saw in Panel B of Table 1 that VCs typically invest larger round amounts than angels. One might argue that companies that needed less investment in the past chose angel financing; to the extent that these companies continue to need less, they are also less likely to want VC funding. As a consequence, one might empirically observe a substitutes pattern that is largely driven by financing needs. To examine whether investment needs can account for the observed pattern in the data, we first include the round amount as a control to the model of Panel B from Table 4 – this is the most natural model to use since it conditions on a positive round amount. In unreported regressions we find that the round amount control itself is highly significant, as expected. More important, the coefficients for the substitutes effects between angels and VCs are hardly affected at all, suggesting that this addition cannot explain away the substitutes result.

To further investigate the effects of round sizes, we then ask whether the substitutes effect differs between smaller versus larger rounds. We divide our sample at the median round size, which is \$250K, and estimate the effect of prior investors types separately for larger and smaller deals. Again we include round size as a direct control. The results are shown in Table 6. We find that the effects on the main diagonal, as well as the substitutes effects between angels and VCs, all continue to apply. All coefficients remaining highly significant at the 1% level, both for large and for small deals. This reaffirms that investment needs cannot explain our main results.

Table 6 also allows us to compare the strength of substitutes effects between large versus small deals. The lower part of Table 6 tabulates the results from a series of t-tests of whether the coefficients differ between large versus small deals. For the effect of having prior VC funding on the amount of angel funding, we find that the coefficient is significantly more negative for large deals than for small deals. As for the effect of having prior angel funding on the amount of VC funding, we find that the coefficient is less negative for large deals than for small deals. However, the difference between coefficients turns out to be relatively small, and remains statistically insignificant. These results suggest that while round sizes cannot explain the main substitutes effects, they may still influence the strength of substitutes effects, especially for the effect of prior VC funding on angel funding.[18]

2.3.6 Decomposing Investor Types

We now turn to a decomposition of our investor types. Our main interest is to understand whether the substitutes effects between angels and VCs applies uniformly across angel types. In section 2, we already discussed a decomposition of angel investors into two types: those that invest in only one company, versus those that invest in multiple companies. We interpret investing in multiple companies as a sign of investor commitment to angel investing.

Theoretically, there can be opposing predictions about the effects of those two types. On the one hand, one may conjecture that more committed angels are a stronger substitute to VCs than single angels, because committed angels are more willing and able to fund companies on their own. On the other hand, venture capitalists may find it easier to work with committed angels, suggesting there would be stronger substitutes effect for single company angels.

Table 7 shows the results for decomposing angels. We find strongly positive coefficients on the main diagonal, suggesting that the positive effects of already having a certain type of investor also continue to apply within the angel decomposition. The most interesting results concern differences in the substitutes effects. Comparing the coefficients for prior VC funding in columns 1 and 2, we note that both coefficients are negative and significant at the 1% level. However, the coefficient in column 1 is almost three times as large as the coefficient in column 2. This suggests a stronger substitutes effect for less committed angels. Furthermore, in column 3 we see that the effect of having prior funding from ‘single company’ angels has a negative and highly significant effect on obtaining VC funding, whilst the effect of prior funding from ‘multiple company’ angels is insignificant. Moreover, the difference between those two coefficients is

[18] Table 6 also suggests some interesting differences in the substitutes patterns with other investors. In particular, there seems to be a strong two-way substitutes effect between angels and other investors for smaller deals. For larger deals, however, having other investors helps with obtaining angel financing.

significant at the 1% level. This suggests that VC funding is less forthcoming only in the presence of ‘single company’ angels, but not in the presence of ‘multiple company’ investors. Overall, these results suggest stronger substitutes effects for less committed angels.

Table 7 also suggests an interesting asymmetry in the relationship amongst angels. Having prior funding from ‘multiple company’ angels seems to facilitate subsequent funding from ‘single company’ angels. However, the reverse is not true, in that prior funding from ‘single company’ angels has no significant effect on subsequent funding from ‘multiple company’ angels. This seems to suggests a hierarchy amongst angels, where less committed angels follow more committed ones, but not vice versa.

Table 8 further decomposes the remaining investor categories. As discussed in section 2, VCs can be subdivided into two groups, namely private VCs and government-supported VC. We also subdivide the other investors category into corporate investors, financial investors, and founders. Table 8 reports a large number of results, here we only discuss the most important ones.

First, we note in columns 3 and 4 that the effect of prior angel funding is very similar to that observed in Table 7. Specifically, we find that having prior funding from ‘single company’ angels is associated with less VC, both for private and government VCs. However, prior funding from ‘multiple company’ angels does not impact subsequent VC funding, neither for private nor government VCs.

Second, we note some interesting differences for obtaining angel funding. In columns 1 and 2 we find that the coefficient for prior funding from government VCs is negative and highly significant, whereas the coefficient for private VCs is smaller and statistically insignificant. This suggests that government VCs are less open than private VCs to adding angel investors in later rounds.

Third, we find complementarities between the two types of VCs, although with an interesting asymmetry. Having prior private VC funding seems to facilitate subsequent government VC funding, with a positive coefficient that is significant at the 1% level. However, for the reverse effect (i.e., the effect of prior government VC funding on subsequent private VC funding) the coefficient remains insignificant. This suggests an asymmetry where government VC follows private VC, but not the other way round. This effect resembles the hierarchical result amongst angel investors discussed in Table 7 (which are also present in Table 8). Finally note that Table 8 contains a large number of coefficients concerning the breakdown of the ‘other investors’ category. However, with most of the coefficients being insignificant, no clear pattern of results emerges.

Overall, we note that the results from Tables 3 - 8 suggest a clear pattern of substitutes effects between angels and VCs. The effects do not appear to be driven by unobserved company heterogeneity or differences in deal sizes. However, the effects are more pronounced for angel investors that only invest in a ‘single company’, than those who invest in multiple companies.

2.4 The Relationship Between Investor Type and Company Performance

In this section, we consider the relationship between the financing patterns and company performance. Our first question concerns the relationship between investor choices and performance. The main issue is whether obtaining funding from different investor translates into different company outcomes. Our second question concerns interactions between angels and VCs. In technical terms, we basically ask whether the outcome function has a supermodular or submodular structure.[19]

For our empirical estimation, we consider a quarterly panel of our sample companies and estimate the following regression model:

$$Y_{kt} = \alpha + \beta_k I_{k,t-1} + \beta_M M_{k,t-1} + \beta_c X_c + \beta_{ct} X_{ct} + \eta_t + \varepsilon_{ct}$$

where the variables are the same as in section 3, with the additions of Y_t and $M_{k,t-1}$. Y_t is the performance of company in period t. We consider a total of five measures, discussed in section 2. $M_{k,t-1}$ is a characterization of interaction effects between the indicator variables $I_{k,t-1}$. In principle there are many potential interaction effects, and many ways of measuring them. We focus on the following ones: In Table 10 we consider an interaction between angels and VCs that consists of the product of prior angel and prior VC investment amounts. In Table 12 we consider two

[19] To make this concrete, consider the following simple specification. Let Y be measure of company performance, and consider two potential inputs, called $a \in \{0,1\}$ for angel investments and $v \in \{0,1\}$for venture capital investments. A supermodular (submodular) production function satisfied the following condition: $Y(a=1,v=1) - Y(a=0,v=1) > (<) Y(a=1,v=0) - Y(a=0,v=0)$.

interaction effects using the same measurement approach, one between 'single company' angels and VCs, the other between 'multiple company' angels and VCs.

Table 9 reports the results from the regressions without interaction effects. We find that VC funding is associated with a higher exit rate, a higher chance of obtaining 'major deals', higher revenues and higher employment. The only outcome regression where VC is insignificant is the probability of death. These results are consistent with prior research on venture capital (see Da Rin, Hellmann and Puri 2013). Prior angel funding is found to have no significant effect on three out of five outcome regressions. Not surprisingly, it has a negative coefficient in the 'Major deal' regression. Maybe more interesting, we find a positive relationship between angel investment and the number of employees. The coefficients for the 'other investors' category are mostly insignificant, except for a significantly lower death rate.

Table 10 adds the interaction effect to examine potential super/submodularity of the outcome function. The results indicate the presence of negative interaction effects, i.e., a submodular production function.[20] The coefficients for exit and 'major deal' are statically significant, the others remain insignificant. This evidence is suggestive albeit certainly not conclusive of the notion that combining angels and VCs is associated with lower performance outcomes.

One important caveat with the outcome analysis concerns endogeneity. The current analysis cannot distinguish between selection effects, where unobserved company heterogeneity is driving both the choice of investors and outcomes, versus treatment effects, where the choice of investor type directly affects outcomes. This limits the interpretation that we can put on both the main effects as well as the interaction effects.[21]

We also redo the analysis of Tables 9 and 10 decomposing angel types. Table 11 considers the model without interactions. The main insight is that 'single company' angels are associated with lower performance outcomes. The coefficient for prior investments from 'single company' angels is lower than the one from 'multiple company' angels in four out of five regressions, with

[20] Death is a negative outcome. A positive coefficient suggests more death, which can be interpreted as a negative interaction effect.

[21] For a useful discussion of how unobserved heterogeneity may affect the estimation of interaction effects, see also Athey and Stern (1998) and Cassiman and Veuglers (2006).

statistical significance in two out of five. Table 12 finally considers the interaction effect for the two angel types with VCs. The interaction term of 'multiple company' angels and VCs is never statistically significant, but the interaction term of 'single company' angels and VCs is negative and statistically significant in the exit and the major deal regressions. However, the (unreported) t-test for the difference between the two interaction terms is never statistically significant. [22]

Overall, we would say that there is suggestive but not conclusive evidence that 'single company' angels experience lower performance outcomes. They also seem to experience more negative interaction effect with VCs than 'multiple company' angels.

2.5 Conclusion

This paper considers the dynamic interaction between different types of investors in entrepreneurial companies, focusing in particular on the interactions between angels and VCs. Using detailed data from British Columbia, Canada, we find considerable support for the hypothesis that angels and VCs are substitutes. Companies that obtain venture capital funding are less likely to obtain subsequent angel funding. Maybe more surprising, the converse is also true, in that companies with prior angel investments are less likely to subsequently obtain venture capital funding. The results seem robust to unobserved heterogeneity across companies, and cannot be explained by differences in investment round size. However, the substitutes effects appear to be stronger for less committed angels that only invest in single company, rather than more committed angels that invest in multiple companies. Venture capital backed companies appear to achieve better outcomes, in terms of exits, revenue growth or employment growth. Combining angel and venture capital investors is also associated with lower exits.

This result is of interest to policy makers. It suggests that mixing angels and VCs may not be as helpful, for the companies and ~~the~~ society, as one might think. This statement appears to be true at least for a certain group of companies. It is thus important for policy makers to identify companies that are best served by both angels and venture capitalists or by either angels or venture capitalists. It is also important for policy makers to assist the entrepreneur to enhance the benefit of having both angels and venture capitalists through education program and so on.

[22] In unreported regression we also added an interaction effect between 'single company' and 'multiple company' angels to the regressions of Table 12, but found that this interaction effect is almost always insignificant.

Our analysis suggests several avenues for future research. One important issue is the possibility of time-varying unobserved heterogeneity among companies. In the absence of true randomization, it remains difficult to cleanly identify causal effects, both for the analysis of investment patterns and company outcomes. More complete data on the interim performance of companies would also help to control for selection effects.

Another important issue would be to obtain a deeper understanding of the reasons behind the observed substitutes pattern. Do angels and VCs have different networks? Do they have incompatible governance systems? Or are disagreements about valuations driving the substitutes result?

Finally, while we exploit a unique opportunity to obtained detailed data on BC angels, it would be interesting to see to what extent the results continue to hold in other environments. For example, does the substitutes also hold in the most advanced entrepreneurial ecosystems, such as Silicon Valley? And what about less developed markets for entrepreneurial finance?

Table 1: Descriptive Statistics

Panel A: Company Descriptive Statistics

This table provides some descriptive statistics at the company level. All variables are defined in Table A1 in the Appendix.

Variable	No. of companies	Mean	Standard Deviation
Age at time of first financing	469	2.4035	3.6490
Age at time of last financing	469	6.2052	4.6677
Age at time of exit / end of sample	469	10.2495	5.8062
Vancouver	469	0.7292	0.4448
Victoria	469	0.0746	0.2631
Okanagan / Thompson	469	0.0512	0.2206
Rest of BC	469	0.1450	0.3525
Software	469	0.2814	0.4502
Biotech	469	0.1215	0.3271
Cleantech	469	0.0533	0.2249
IT&Telecom	469	0.0704	0.2560
High-tech Manufacturing	469	0.1791	0.3838
High-tech Services	469	0.0597	0.2372
Tourism	469	0.0768	0.2665
Other Industries	469	0.1578	0.3649
Exit	469	0.1301	0.3367
Death	469	0.2260	0.4187
Major Deal	469	0.0810	0.2732
Revenues ($M)	334	3.6956	12.2425
Employees	275	16.9755	22.4588

Table 1: Descriptive Statistics (continued)

Panel B: Investor Descriptive Statistics – Current Investments

This table provides some descriptive statistics about investor involvement in company-quarters (aka "investment rounds"). All variables are defined in Table A1 in the Appendix.

Panel (# company-quarters)	Full panel (n=7248)	Round sample (n=2188)
Investor category	Fraction of rounds	Per-round amounts
Any investor	30.04%	$2,201,803
Angel	20.85%	$256,041
VC	9.51%	$1,753,973
Other	10.38%	$191,789
Angel Single	16.86%	$177,571
Angel Multiple	7.70%	$73,135
VC Private	4.41%	$594,698
VC Government	7.84%	$1,159,275
Other Corporate	6.08%	$114,289
Other Financial	2.30%	$39,739
Other Founders	6.43%	$37,763

Panel C: Investor Descriptive Statistics – Cumulative Investments

This table provides some descriptive statistics about cumulative investments amounts. All variables are defined in Table A1 in the Appendix.

Investor category	Percentage of companies (after last financing round)	Amounts per company (after last financing round)
Any investor	100.00%	$10,271,950
Angel	84.65%	$1,194,493
VC	37.53%	$8,182,714
Other	55.86%	$894,746
Angel Single	75.69%	$853,300
Angel Multiple	49.90%	$341,193
VC Private	26.65%	$2,774,414
VC Government	31.98%	$5,408,300
Other Corporate	40.51%	$533,184
Other Financial	23.88%	$185,391
Other Founders	37.74%	$176,171

Table 2: Company Characteristics and Investor Types

This table reports results from panel OLS regressions. The unit of analysis is the company. The dependent variables are the investment amounts of Angel, VC and Other investors in the first quarter (for columns 1-3) and across all rounds (for columns 4-6). The main independent variables are company age at first round, industry dummies and region dummies. The unreported control variables are non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	First Round			All Rounds		
	1	2	3	4	5	6
Investment Amount	Angel	VC	Other	Angel	VC	Other
Age at First Round	-0.0344	0.158	0.00688	-0.0855	0.229*	-0.0278
	(0.118)	(0.131)	(0.0937)	(0.107)	(0.135)	(0.118)
Victoria	0.255	-0.508	1.089	-0.898	0.764	-0.358
	(1.715)	(1.731)	(1.355)	(1.675)	(2.084)	(1.613)
Okanagan Thomson	0.769	1.817	1.932	-0.682	0.149	2.016
	(1.525)	(1.749)	(2.195)	(1.730)	(1.873)	(2.296)
Rest of BC	0.713	-2.381**	0.257	1.743*	-5.117***	0.432
	(1.176)	(1.012)	(1.109)	(0.959)	(1.264)	(1.355)
Biotech	-1.111	2.679*	-0.755	-1.048	4.788***	-1.135
	(1.431)	(1.588)	(1.517)	(1.333)	(1.808)	(1.662)
Cleantech	2.621*	-3.805***	0.793	1.516	-2.082	-2.671
	(1.553)	(1.426)	(1.929)	(1.169)	(1.983)	(2.202)
IT&Telecom	-1.827	0.209	-1.666	-0.701	1.090	-1.703
	(1.884)	(1.896)	(1.609)	(1.732)	(2.157)	(2.012)
High-tech Manufacturing	2.082*	-0.471	-0.807	1.687	-0.987	-2.057
	(1.201)	(1.363)	(1.232)	(1.160)	(1.512)	(1.400)
High-tech Services	1.744	-3.449*	-2.609	1.695	-4.907**	-5.494**
	(1.732)	(1.821)	(1.946)	(1.755)	(2.234)	(2.165)
Tourism	0.702	-5.215***	-1.108	2.992**	-6.949***	-3.902**
	(1.844)	(1.243)	(1.692)	(1.392)	(1.415)	(1.958)
Other industry	2.860**	-2.722**	-4.206***	3.480***	-5.019***	-5.440***
	(1.306)	(1.298)	(1.245)	(1.181)	(1.479)	(1.459)
Controls	YES	YES	YES	YES	YES	YES
Observations	469	469	469	469	469	469
Number of Companies	469	469	469	469	469	469
R-squared	0.234	0.238	0.291	0.200	0.390	0.293

Table 3: The Effect of Prior Investor Choices on Current Investor Choices

This table reports results from panel OLS regression. The unit of analysis is company-quarter. The dependent variables are the current investment amounts for Angel, VC, Other and All investors. The main independent variables are the prior cumulative investments amounts of Angel, VC, and Other investors. Further reported independent variables are age at first round, region dummies, and industry dummies. The unreported control variables are non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DV: Current Investment Amounts			
Prior Cumulative	1	2	3	4
Investment Amount	Angel	VC	Other	All
Angel	0.109***	-0.0378***	-0.00804	0.0188
	(0.0121)	(0.0119)	(0.0106)	(0.0163)
VC	-0.0843***	0.160***	-0.0192**	0.0254*
	(0.0113)	(0.00956)	(0.00950)	(0.0139)
Other	0.0101	-0.000494	0.102***	0.0139
	(0.0103)	(0.00874)	(0.00789)	(0.0120)
Age at First Round	-0.0191	0.0202	-0.0169	0.00882
	(0.0259)	(0.0173)	(0.0188)	(0.0313)
Victoria	0.358	0.103	0.187	0.192
	(0.302)	(0.189)	(0.179)	(0.307)
Okanagan Thomson	0.969***	0.0155	0.464	1.231***
	(0.371)	(0.294)	(0.435)	(0.435)
Rest of BC	0.286	-0.396***	-0.210	-0.155
	(0.350)	(0.146)	(0.224)	(0.337)
Biotech	0.0352	-0.374	0.143	-0.405
	(0.276)	(0.287)	(0.252)	(0.340)
Cleantech	-0.319	0.0617	-0.582*	-0.793
	(0.564)	(0.276)	(0.348)	(0.489)
IT&Telecom	-0.126	0.169	-0.175	-0.168
	(0.349)	(0.401)	(0.264)	(0.514)
High-tech Manufacturing	0.0519	-0.00827	0.220	-0.0518
	(0.298)	(0.217)	(0.223)	(0.339)
High-tech Services	-0.234	-0.468**	-0.235	-0.549
	(0.391)	(0.203)	(0.338)	(0.434)
Tourism	-0.0322	-0.482**	-0.154	-0.105
	(0.427)	(0.207)	(0.331)	(0.409)
Other industry	0.168	-0.268	-0.211	0.0813
	(0.315)	(0.193)	(0.216)	(0.329)
Controls	YES	YES	YES	YES
Observations	6,815	6,815	6,815	6,815
Number of companies	469	469	469	469

Table 4: Decomposing Current Investor Choices

Panel A: The effect of prior investor choices on whether or not a round occurs

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The dependent variables are dummy variables for the presence of Angel, VC and Other investors in the current quarter. The main independent variables are the prior cumulative investments amounts of Angel, VC, and Other investors. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DV: Dummy variable for whether investment made			
	1	2	3	4
Prior Cumulative Investment Amounts	Angel	VC	Other	Any investment
Angel	0.00551***	-0.00179***	-0.000545	0.000933
	(0.000651)	(0.000566)	(0.000567)	(0.000810)
VC	-0.00492***	0.00770***	-0.00136***	0.000113
	(0.000619)	(0.000456)	(0.000510)	(0.000707)
Other	0.000415	-7.08e-05	0.00552***	0.000514
	(0.000562)	(0.000419)	(0.000424)	(0.000622)
Controls	YES	YES	YES	YES
Observations	6,815	6,815	6,815	6,815
Number of companies	469	469	469	469

Table 4 (continued): Decomposing Current Investor Choices

Panel B: The effect of prior investor choices on round amounts
(conditional on a round occurring)

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The sample is conditioned on having a positive investment amount in a quarter. The dependent variables are the investment amount of Angel, VC and Other investors. The main independent variables are the prior cumulative investments amounts of Angel, VC, and Other investors. Unreported control variables are industry, region, company age at first round, company age at time of investment, time since last investment, calendar time, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DV: Current Investment Amount (Conditional on there being a round investment)			
	1	2	3	4
Prior Cumulative Investment Amounts	Angel	VC	Other	Total
Angel	0.397***	-0.205***	-0.0840**	0.00188
	(0.0359)	(0.0311)	(0.0357)	(0.0113)
VC	-0.307***	0.568***	-0.101***	0.0786***
	(0.0324)	(0.0325)	(0.0312)	(0.00926)
Other	0.0184	-0.0485**	0.345***	0.00295
	(0.0230)	(0.0209)	(0.0291)	(0.00721)
Controls	YES	YES	YES	YES
Observations	1,719	1,719	1,719	1,719
Number of companies	469	469	469	469

Table 5: Current Investor Choices with Company Fixed Effect Regressions

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The dependent variables are the current investment amounts for Angel, VC, Other and All investors. The main independent variables are the prior cumulative investments amounts of Angel, VC, and Other investors. The unreported control variables are company, industry, region, company age at first round, company age at time of investment, time since last investment, calendar time, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DV: Current Investment Amount			
	1	2	3	4
Prior Cumulative Investment Amounts	Angel	VC	Other	Total Investment
Angel	-0.0372	-0.0409*	-0.0552*	-0.0673
	(0.0457)	(0.0209)	(0.0306)	(0.0523)
VC	-0.110***	0.0163	-0.0400*	-0.0660*
	(0.0276)	(0.0235)	(0.0225)	(0.0347)
Other	-0.00655	-0.000309	-0.0890***	-0.00561
	(0.0304)	(0.0239)	(0.0254)	(0.0400)
Controls	YES	YES	YES	YES
Observations	6,815	6,815	6,815	6,815
R-squared	0.101	0.074	0.048	0.113
Number of companies	469	469	469	469

Table 6: Current Investor Choices by Deal Sizes

This table reports results from panel OLS regressions. The unit of analysis is company-quarter and the sample is conditioned on a positive investment round in the quarter. The dependent variables are the current investment amounts for Angel, VC, Other and All investors. The main independent variables are the prior cumulative investments amounts of Angel, VC, and Other investors, as well as the total current investment amount. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DV: Current Investment Amount		
	1	2	3
Prior Cumulative Investment Amounts	Angel	VC	Other
Angel (Large Deals)	0.353***	-0.177***	-0.0624
	(0.0420)	(0.0312)	(0.0413)
VC (Large Deals)	-0.414***	0.495***	-0.256***
	(0.0329)	(0.0305)	(0.0333)
Other (Large Deals)	0.0897***	-0.0948***	0.358***
	(0.0304)	(0.0265)	(0.0376)
Angel (Small Deals)	0.399***	-0.234***	-0.173***
	(0.0441)	(0.0453)	(0.0429)
VC (Small Deals)	-0.261***	0.394***	-0.146***
	(0.0360)	(0.0350)	(0.0359)
Other (Small Deals)	-0.0680**	-0.0111	0.263***
	(0.0276)	(0.0232)	(0.0311)
Total Current Investment Amount	0.371***	1.529***	1.380***
	(0.104)	(0.141)	(0.138)
Controls	YES	YES	YES
Angel (Large vs. Small Deals)	-0.046	0.057	0.1106**
	(0.85)	(1.33)	(5.01)
VC (Large vs. Small Deals)	-0.153***	0.101***	-0.11***
	(32.14)	(17.82)	(11.96)
Other (Large vs. Small Deals)	0.1577***	-0.0837**	0.095**
	(17.76)	(6.31)	(6.47)
Observations	1,719	1,719	1,719
Number of companies	469	469	469

Table 7: Decomposing Angel Investors

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The dependent variables are the current investment amounts for Angel-Single, Angel-Multiple, VC, Other and All investors. The main independent variables are the prior cumulative investments amounts of Angel-Single, Angel-Multiple, VC, and Other investors. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DV: Current Investment Amount			
	1	2	3	4
Prior Cumulative Investment Amounts	Angel - Single	Angel - Multiple	VC	Other
Angel-Single	0.0335**	0.00111	-0.0409***	0.00546
	(0.0150)	(0.0119)	(0.0101)	(0.00961)
Angel-Multiple	0.0275*	0.0687***	-0.00299	-0.00539
	(0.0145)	(0.0124)	(0.00811)	(0.00818)
VC	-0.0837***	-0.0284***	0.159***	-0.0137
	(0.0125)	(0.0105)	(0.00931)	(0.00911)
Other	0.0356***	0.00426	0.00340	0.102***
	(0.0107)	(0.00852)	(0.00865)	(0.00820)
Controls	YES	YES	YES	YES
Angel (Single vs. Angel)	0.006	-0.06759***	-0.03791***	0.01085
	(0.01)	(10.67)	(8.61)	(0.72)
Observations	6,815	6,815	6,815	6,815
Number of companies	469	469	469	469

Table 8: Decomposing all Investor Categories

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The dependent variables are the current investment amounts for all investor categories. The main independent variables are the prior cumulative investments amounts for all investor categories. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DV: Current Investment Amount						
	1	2	3	4	5	6	7
Prior Cumulative Investment Amounts	Angel - Single	Angel - Multiple	Private VC	Government VC	Corporate Investor	Financial Investor	Founders
Angel - Single	0.0251*	0.000681	-0.0226***	-0.0328***	-0.00349	0.000900	-0.00936
	(0.0151)	(0.0118)	(0.00826)	(0.00967)	(0.00718)	(0.00399)	(0.00729)
Angel - Multiple	0.0258*	0.0694***	9.84E-05	-0.00261	-0.0102	-0.00171	-0.00705
	(0.0147)	(0.0126)	(0.00512)	(0.00784)	(0.00631)	(0.00418)	(0.00650)
Private VC	-0.0153	-0.0126	0.0800***	0.0343***	0.00968	-0.00477	-0.00498
	(0.0111)	(0.00985)	(0.0108)	(0.0133)	(0.00812)	(0.00499)	(0.00586)
Government VC	-0.0750***	-0.0219**	0.00438	0.134***	-0.0127*	0.00178	-0.0198***
	(0.0114)	(0.0103)	(0.00948)	(0.0118)	(0.00769)	(0.00466)	(0.00567)
Corporate Investor	0.0111	-0.00646	0.0101	0.000216	0.0737***	0.00553	0.0128*
	(0.0120)	(0.0102)	(0.00746)	(0.00882)	(0.00795)	(0.00433)	(0.00747)
Financial Investor	-0.00184	-0.00539	-0.00142	-0.000696	0.00623	0.0172***	-0.00544
	(0.0162)	(0.0152)	(0.00856)	(0.0109)	(0.0111)	(0.00642)	(0.00990)
Founders	0.0511***	0.0135	0.00433	-0.00786	0.0287***	0.0147***	0.0873***
	(0.0136)	(0.0114)	(0.00552)	(0.00754)	(0.00848)	(0.00429)	(0.00812)
Controls	YES	YES	YES	YES	YES	YES	YES
Observations	6,815	6,815	6,815	6,815	6,815	6,815	6,815
Number of companies	469	469	469	469	469	469	469

Table 9: The Relationship between Investor Choices and Company Outcomes

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The dependent variables are the Exit, Death and Major Deal dummies (which are also scaled by a factor of 1000 to obtain easily readable coefficients), as well as revenues and employees. The main independent variables are the prior cumulative investments amounts of Angel, VC, and Other investors. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5
Prior Cumulative Investment Amounts	Exit	Death	Major Deal	Revenue	Employees
Angel	-0.202	-0.00151	-0.450***	-0.0329	0.0147*
	(0.145)	(0.107)	(0.165)	(0.0216)	(0.00843)
VC	0.391***	-0.0397	0.352***	0.0408**	0.0133**
	(0.0958)	(0.0844)	(0.107)	(0.0190)	(0.00573)
Other	0.0158	-0.178**	-0.000617	-0.000952	-0.00469
	(0.0944)	(0.0796)	(0.0991)	(0.0218)	(0.00824)
Revenues - one year lagged				0.0563	
				(0.0433)	
Employees - one year lagged					0.214***
					(0.0558)
Controls	YES	YES	YES	YES	YES
Angel vs. VC	-0.594***	0.03819	-0.802***	-0.0737***	0.0014
	(16.92)	(0.11)	(17.08)	(7.04)	(0.02)
Observations	14,719	14,719	13,769	4,083	2,339
Number of companies	469	469	462	302	202

Table 10: Interaction Effects between Angels and VCs on Company Outcomes

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The dependent variables are the Exit, Death and Major Deal dummies (which are also scaled by a factor of 1000 to obtain easily readable coefficients), as well as revenues and employees. The main independent variables are the prior cumulative investments amounts of Angel, VC, and Other investors, as well as the interaction term between angel and VC investors. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5
Prior Cumulative Investment Amounts	Exit	Death	Major Deal	Revenue	Employee
Angel * VC	-0.0236**	0.00329	-0.0273*	-0.00269	-0.00118
	(0.00934)	(0.00983)	(0.0149)	(0.00197)	(0.000802)
Angel	-0.327*	0.0121	-0.684***	-0.0520**	0.00389
	(0.185)	(0.117)	(0.246)	(0.0265)	(0.0106)
VC	0.307***	-0.0277	0.263***	0.0354*	0.0118**
	(0.106)	(0.0914)	(0.102)	(0.0201)	(0.00601)
Other	0.0478	-0.182**	0.0456	0.00171	-0.00181
	(0.0978)	(0.0821)	(0.104)	(0.0216)	(0.00871)
Revenues - one year lagged				0.0570	
				(0.0435)	
Employees - one year lagged					0.211***
					(0.0558)
Controls	YES	YES	YES	YES	YES
Observations	14,719	14,719	13,769	4,083	2,339
Number of companies	469	469	462	302	202

Table 11: Company Outcomes: Decomposing Angel Investors

This table reports results from panel OLS regression. The unit of analysis is company-quarter. The dependent variables are the Exit, Death and Major Deal dummies (which are also scaled by a factor of 1000 to obtain easily readable coefficients), as well as revenues and employees. The main independent variables are the prior cumulative investments amounts of Angel-Single, Angel-Multiple, VC, and Other investors. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5
Prior Cumulative Investment Amount	Exit	Death	Major Deal	Revenue	Employee
Angel – Single	-0.348***	-0.0124	-0.296***	-0.0404*	0.0108
	(0.119)	(0.105)	(0.115)	(0.0214)	(0.00913)
Angel – Multiple	0.0469	0.0305	-0.165**	0.0170	0.00375
	(0.0887)	(0.0846)	(0.0778)	(0.0165)	(0.00618)
VC	0.326***	-0.0446	0.395***	0.0358*	0.0129**
	(0.0919)	(0.0873)	(0.111)	(0.0189)	(0.00596)
Other	0.0582	-0.180**	0.0341	-0.000711	-0.00561
	(0.0943)	(0.0819)	(0.101)	(0.0214)	(0.00885)
Revenues - one year lagged				0.0564	
				(0.0435)	
Employees - one year lagged					0.211***
					(0.0560)
Controls	YES	YES	YES	YES	YES
Angel (Single vs. Multiple)	-0.3949***	-0.0429	-0.131	-0.0574*	0.00705
	(6.85)	(0.08)	(1.52)	(3.07)	(0.31)
Angel-Single vs. VC	-0.674***	0.0322	-0.691***	-0.0762***	-0.0021
	(26.76)	(0.09)	(18.76)	(8.21)	(0.05)
Angel-Multiple vs. VC	-0.2791**	0.0751	-0.56***	-0.0188	-0.00915
	(4.28)	(0.33)	(15.48)	(0.5)	(0.93)
Observations	14,719	14,719	13,769	4,083	2,339
Number of companies	469	469	462	302	202

Table 12: Company Outcomes with Interaction Effects: Decomposing Angel Investors

This table reports results from panel OLS regressions. The unit of analysis is company-quarter. The dependent variables are the Exit, Death and Major Deal dummies (which are also scaled by a factor of 1000 to obtain easily readable coefficients), as well as revenues and employees. The main independent variables are the prior cumulative investments amounts of Angel-Single, Angel-Multiple, VC, and Other investors, as well as the interaction terms between Angel-Single and VC investors, and between Angel-Multiple and VC investors. The unreported control variables are company age at first round, industry dummies, region dummies, non-parametric clocks for calendar time and the time since the last investment, as well as the constant. All variables are defined in Table A1 in the Appendix. All investment amounts are in natural logarithm. Robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5
Prior Cumulative Investment Amount	Exit	Death	Major Deal	Revenue	Employee
Angel - Single * VC	-0.0244**	-0.00226	-0.0194*	-0.000780	-0.00104
	(0.0116)	(0.00985)	(0.0105)	(0.00179)	(0.000699)
Angel - Multiple * VC	0.00489	0.00475	-0.00880	-0.000532	0.000448
	(0.0112)	(0.00831)	(0.00963)	(0.00156)	(0.000510)
Angel – Single	-0.602***	-0.0612	-0.490***	-0.0442	-0.00227
	(0.213)	(0.148)	(0.188)	(0.0301)	(0.0115)
Angel – Multiple	0.189	0.104	-0.254	0.0100	0.0121
	(0.237)	(0.157)	(0.200)	(0.0278)	(0.00943)
VC	0.201*	-0.0166	0.199	0.0293	0.0124*
	(0.118)	(0.108)	(0.126)	(0.0221)	(0.00728)
Other	0.0742	-0.182**	0.0740	-2.69e-05	-0.00459
	(0.0965)	(0.0827)	(0.104)	(0.0213)	(0.00895)
Revenues - one year lagged				0.0557	
				(0.0439)	
Employees - one year lagged					0.212***
					(0.0562)
Controls	YES	YES	YES	YES	YES
Observations	14,719	14,719	13,769	4,083	2,339
Number of companies	469	469	462	302	202

Table A1: Variable definitions

Investor categories

All investment amounts are in natural logarithm of one cent plus the investment amount.

Variable	Description
(a) Investor categories	
ANGEL	an angel investor
ANGEL-SINGLE	an angel investor who invests in only one company.
ANGEL-MULTIPLE	an angel investor who invests in more than one companies.
VC	an venture capital firm
PRIVATE VC	a private venture capital firm.
GOVERNMENT VC	a government venture capital firm, including all retail VCCs
CORPORATE INVESTOR	an operational corporation that invests
FINANCIAL INVESTOR	a financial institution or other entity that invests
FOUNDERS	shareholders who are either founders, family of founders, or employees of the company

Dependent variables.

All investment amounts are in natural logarithm of one plus investment amounts.

Variable	Description
(a) Investor choices	
FIRST ROUND	investment amount made by alternative categories of investor at time of first financing. The relevant categories are defined in the investor categories section of this table.
LAST ROUND	investment amount made by alternative categories of investor at time of last financing. The relevant categories are defined in the investor categories section of this table.
CURRENT	investment amount made by alternative categories of investor in a given financing round. The relevant categories are defined in the investor categories section of this table.
TOTAL – CURRENT	investment amount made by all investors in a given financing round.
DUMMY – CURRENT	dummy variables that takes on a value of 1 if a company received financing from one of the following categories of investor in a given financing round. The relevant categories are defined in the investor categories section of this table.

Table A1 (continued)	
(b) Outcomes	
EXIT	dummy variable that takes on a value of 1 if the company has been exited by December 2012 via an IPO or acquisition; 0 otherwise. The data is obtained from the SDC Global News Issue, SDC Merger, SEDAR, and from web searches
DEATH	dummy variable that takes on a value of 1 if by December 2012 the company has gone out of business; 0 otherwise. The data is obtained from BC Registry, and from web search.
MAJOR DEAL	dummy variable that takes on a value of 1 if a company received a more than 10M in funding in a given financing round.
REVENUE	natural logarithm of the company's revenues in dollars plus 1 dollar.
EMPLOYEES	natural logarithm of the number of employees plus 1.

Independent variables.
All investment amounts are in natural logarithm of one plus investment amounts.

Variable	Description
(a) Investments	
PRIOR	cumulative investment amount made by alternative categories of investor prior to a given quarter. The relevant categories are defined in the investor categories section of this table.
(b) Interaction terms	
Investor k (LARGE DEALS)	interaction term between Investor k - PRIOR and LARGE. LARGE is a dummy variable that takes on a value of 1 if a deal has an investment amount greater than the median investment amount; 0 otherwise. k stands for the investor categories defined above.
Investor k (SMALL DEALS)	interaction term between Investor k - PRIOR and SMALL. SMALL is a dummy variable that takes on a value of 1 if a deal has an investment amount less than or equal to the median investment amount; 0 otherwise. k stands for the investor categories defined above.
ANGEL * VC	interaction term between ANGEL PRIOR and VC PRIOR.
ANGEL - SINGLE * VC	interaction term between ANGEL - PRIOR - SINGLE and VC - PRIOR
MULTIPLE - SINGLE * VC	interaction term between ANGEL - PRIOR - MULTIPLE and VC - PRIOR

Table A1 (continued)	
(c) Company characteristics	
REVENUES - ONE YEAR	natural logarithm of one plus the previous year (4 quarters) revenue.

LAGGED EMPLOYEES - ONE YEAR LAGGED	natural logarithm of one plus the previous year (4 quarters) number of employees.
INDUSTRY	set of mutually exclusive dummy variables that takes on a value of 1 if the company is reported to operate in one of the following industries; 0 otherwise. Our data gives the following options: Biotech; Cleantech; IT & Telecom; Hi-tech Manufacturing; Hi-tech Services; Tourism; Non Hi-tech Industry; Other industry.
LOCATIONS	set of mutually exclusive dummy variables that takes on a value of 1 if the company is reported to operate in one of the following locations; 0 otherwise. Our data gives the following options: Vancouver (GVRD); Victoria (CRD); Okanagan/Thomson V.; Rest of BC.
(d) Control variables	
AGE AT TIME OF FIRST FINANCING	natural logarithm of the company's age measured at time of first financing plus 0.25 (in years).
AGE AT TIME OF FINANCING	natural logarithm of the company's age measured at current round plus 0.25 (in years).
AGE AT TIME OF LAST FINANCING	natural logarithm of the company's age at time of last financing plus 0.25 (in years).
AGE AT TIME OF EXIT	natural logarithm of the company's age at the time of exit plus 0.25 (in years).
TIME SINCE LAST FINANCING	number of quarters since last financing.
COMPANY FIXED EFFECTS	set of 469 dummy variables, one for each company.

Chapter 3: The Geography of Angel Investments

3.1 Introduction

Angel investment is the largest source of risk financing for high-growth early stage entrepreneurial firms (Mason and Harrison, 1996). In fact, estimates in the UK and the US suggest that angels supply an annual financing of two to five times more than that of the venture capitalists to early stage ventures (Wetzel, 1987; Freear et al., 1996; Mason and Harrison, 1993). More recently, Wiltbank (2005a) reports that U.S. angels invest approximately $6 billion into early stage ventures in 2004. This makes the $330 million, as reported in the same study, invested by the venture capitalist into early stage ventures in the same year look unimportant.

In spite of its importance, many features of the angel capital market are not well studied. Among others, the geography of angel investment stands out to be one of the most interesting aspects. Unfortunately, it is also one the least well understood. It is the case because academics and practitioners commonly view the angel capital market as a local market, where local angels invest into local ventures. However, some studies have shown that this is not entirely accurate. As shown in Freear et al. (1992), 36% of angel investments in Connecticut and Massachusetts are made into ventures located over 480 km away from the angel's home or office. As reported by the same authors, this portion of (long) distant angels is of the same size as the size of the, so called, local angels, who invest into ventures located within 80km from the angel's home or office. Although some other studies have shown a greater portion of local angel investments ranging from 50% to 87%, these studies have also recognized that distant angel investments exist and constitute a significant share of all angel investments (Wetzel, 1981; Riding et al., 1993; Mason and Harrison, 1994).

This observation raises an interesting question. What is the role of geographic distance in the angel capital market? Unlike previous studies that documented the role of distance on the angel's investment decision, i.e. local vs. distant investments, this paper systematically looks at the effect of distance on the angel investment performance. Specifically, this paper asks: does geographic distance matter to the return of angel investment?

This study finds that there is a positive and significant relationship between distance and the return to angel investment. An increase in distance from the 25th percentile to the 75th percentile increases the return to angel investment by 6 percentage points.

There are four effects determining the relationship between distance and the return to angel investment. These effects can be grouped into two distinct stages: the selection stage and the value-added stage.

In the selection stage, the effect of distance on the return to angel investment depends on the *quantity* and the *quality* of the information that the angels have about the potential ventures. On one hand, the literature suggests that local investors have an information advantage over distant investors and thus can make an *informed* investment decision. In particular, Stein (2002) states that close-by investors can acquire "*soft*" information through face-to-face interactions with the entrepreneur. Hockberg and Rauh (2012), in explaining the local-bias among public pension, suggest that public pension funds use local connections, networks and political access to gain better information on the prospects of funds located in their home-states. Since the quantity of (soft) information decreases in distance, there is a negative relationship between distance and investment performance. I will refer this effect to as the *information effect* of distance.

On the other hand, local investors may also be influenced by the entrepreneur's over-optimism. It has been documented that over-optimism is very common among entrepreneurs. For example, Moskovitz and Vissing-Jorgensen (2002) find that overoptimism is one of the reasons why an individual becomes an entrepreneur. It has also been reported that over-optimism is associated with fewer work hours, stronger reference toward risky investment, and less prudent financial habits such as saving (Puri and Robinson, 2007). These behaviors may have a harmful impact on the company's performance and thus the investor's return. It could be that the entrepreneur's over-optimism rubs off on investors and particularly strongly on local investors who presumably have more frequent face-to-face meetings with the entrepreneur and other company officials or employees. If so, then in line with Puri and Robinson there would be a predicted positive relationship between distance and investment performance. This will be referred to as the *objectivity effect* of distance.

In the value-added stage, the effect of distance depends on the (types of) value-added services that an investor can provide to the early-stage ventures. This paper considers two types of value added services: monitoring/advising and network. With respect to the monitoring/advising service, it is an established result that monitoring is a productive input provided by the venture capitalists to the entrepreneurial companies (Lerner, 1995; Hellmann and Puri, 2002; Kaplan and Stromberg, 2004). In the context of angel capital, the productive input of angels is usually called "advice". Wong et. al. (2009) suggest that a local presence allows angels to contribute easily to their investee companies. Since "advising" is costly over long distance, distance has a negative relationship with investment performance. This is referred as the *advising effect* of distance.

Regarding the network service, investors can possibly be valuable to the companies through a form of an expanded network. Specifically, investors may often bring in valuable connections that would allow the company to attract follow-on finance. This argument is based on Sorensen and Stuart's work in 2001. The authors argue that, in the absence of public channel of information, entrepreneurs have to rely on their personal and professional network to disseminating timely and reliable information to potential investors. Since expended network is positively related to distance, under this argument, distance has a positive relationship with investment performance. This is the *network effect* of distance.

This paper uses a novel set of data derived from the British Columbia Venture Capital Program to examine the role of distance on the angel investment performance. This rare set of data contains detailed information of all investments, including angel investments, made into early-stage ventures registered under the British Columbia Venture Capital Program between 1999 and 2006.

This data allows me to compute the annualized internal rate of return (AIRR) for both exited and active angel investments. The AIRR is used as main performance measure for three reasons. First, the IRR is the most commonly used measure of return by academics and practitioners (Da Rin et al. 2013). In addition, the simplicity of the majority of angel investments in the sample lessens many of the disadvantages associated with the use of the IRR[23]. And finally, the

[23] One major criticism is that the IRR assumes the interim cash flows can be reinvested at the IRR itself. Consequently, the IRR overstates the effective rate of return when the IRR is high. The reverse is true when the IRR is low. In this case the IRR understates the effective rate of return. This is not so much a concern in our case because (i) interim

inclusion of both realized (exited investment) and unrealized return (active investment) is necessary to reduce potential selection bias. As argued in Cochrane (2005) Korteweg and Sorensen (2010), valuations of companies are observed only when the companies exited. These events are more frequent for either well-performing companies in case of IPOs and acquisitions or low-performing companies in case of failure. Thus the inclusion of active companies should help reducing this selection bias.

Regarding distance, this paper uses three groups of variables: (i) location indicators for the investors and the investee companies; (ii) travel distance in kilometers; and (iii) travel time in seconds. These measures are acquired by feeding each investor-investee pair's geocode to an open source routing software based on Open Street Map.

This paper reports several important findings. First there is a positive relationship between distance and angel investment performance, measured by the annualized internal rate of return. In particular, holding all else constant, an increase in distance from the 25th percentile to the 75th percentile increases (or from 9.34km to 124km) the return to angel investment by 6 percentage points. Second, the effect of distance varies across different categories of angels. This study reports that distance matters more to the less experienced angels, who invest in only one company in the entire dataset. Third, the effect of distance differs for companies located in a center and for companies located in the periphery. Specifically, this paper shows that distance matters more for companies located in Greater Vancouver Capital Region (GVRD) – the main financial and technology center in British Columbia. Furthermore, this paper provides evidence that the relationship between distance and return is determined mostly at the selection stage, where the objectivity effect dominates the information effect. Finally, this study reports that the return to angel investment is highly skewed with 55% of all angel deals result in a break-even or loss and only 22% of all deals result in a positive return of 50% or more.

This paper contributes to two areas of the literature: (i) the literature on the role of distance in the angel capital market, and more generally in corporate finance, and (ii) the literature on the performance of angel investments.

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positive cash flow rarely exists because dividend is uncommon when the company is at its early stage, and (ii) the most common stream of cash flow in this data has includes only one investment moment and one exit moment.

The role of distance has been documented in many areas of the corporate finance literature. For example, Petersen and Rajan (2002), Berger et al. (2005) and Agarwal and Hauswald (2010) find that distance is an important factor of the bank's lending decision. Lerner (1995) and Sorenson and Stuart (2001) find that distance is an important determinant of the propensity to invest and of the VC firm's board membership.

Although being the main source of the external financing for high growth early-stage ventures, there is a limited number of studies on the role of distance in the angel capital market. Furthermore, these studies mostly concentrate on the role of distance on the investment decision. For example, these studies suggest that angels have no strong preference toward local ventures (Freear et. al. 1992; Coveney and Moore 1998; van Osnabrugge and Robinson 2000). Specifically, Wetzel (1981) reported that 24% to 40% of angels claimed that they had no geographical preferences. Similarly, Riding and his co-authors documented in their 1993 study that 36% of Ottawa angels imposed no geographical limits on their investments.

These studies clearly question the commonly used "local market" notion in the angel capital market. More importantly, this demands a re-assessment of the role of distance in the angel capital market, especially on the performance of angel investors. To my knowledge, this study is the first to systematically examine the role of distance on the return to angel investment.

The literature on the angel investment performance is also limited. Indeed, "knowledge about returns on informal investment is mainly folklore or is based on relatively small self-reported samples" (Bygrave and Hunt, 2008). Mason and Harrison (2002b) are among the first to look into the return to angel investment using data acquired from a survey of 51 U.K. angels who made a total of 128 exits. The authors found that 34% of the investments resulted in complete loss, 13% broken-even, and 23% had an IRR of 50% or more among 51 angels who had made a total of 128 exits in U.K. Wiltbank (2005b) used 121 responses from 13 angel groups in the U.S. In total, these angel investors had exited from 414 investments from a total of 1038 investments. The author found that 61.5% of the investment resulted in negative IRR, and only 23.5% had an IRR exceeding 50%. Similar result was found in his later joint work (Wiltbank and Boeker, 2007).

It is important to note that these studies documented realized return as reported by the angel investors. This paper makes an important contribution to this branch of the literature as the first study to systematically compute the return, both realized and unrealized, to the angel investments.

Endogeneity issue is an important concern with this study. It could be the case that entrepreneurs may choose to locate in a particular place (in Vancouver for example) that could give them the best access to the angel capital market. This decision may be based on unobservable company and entrepreneur characteristics. In addition, even if the company location were exogenous, a match between an angel and a company might still be determined by unobservable variables. For examples, a company managed by an established management team could be more prone to have an extensive network that makes it popular to distant investor while it is at the same time more likely to be successful. This example shows that a positive relationship between distance and return could possibly be driven by unobservable company or investor characteristics.

To address endogeneity issues, one would normally need to come up with a valid instrumental variable. In this context, this instrumental variable (for distance) must be correlated with distance and must only be correlated with return through its correlation with distance (exclusion restriction). Instruments that can satisfy both of these conditions are typically hard to find. Consequently, this paper takes an alternative approach in which the selection effect and the treatment effect are built into the hypotheses. I will argue that the strength of the hypothesized effects can expected to differ across angel investor types and company location. Hence, this paper makes use of the richness of our data to attempt to separate out the selection effect from the treatment effect. Nevertheless, in the absence of a valid instrumental variable, one should interpret the result carefully.

The rest of the paper is organized as follows: Section 2 discusses the main effects. Section 3 provides detailed descriptions of the data and presents descriptive statistics. Section 4 reports the results on the role of distance. I conclude in Section 5.

3.2 Hypotheses

Section 2.1 first discusses in detailed the main effects of distance on angel investment performance. Section 2.2 discusses how these effects differ across categories of angels and across company's and angel's locations.

3.2.1 Main Effects of Distance

As pointed out earlier, there are four effects that determine the relationship between distance and angel investment performance. These effects can be grouped into two distinct investment stages: selection stage and the value-added stage.

The Information effect: the quality of the venture selected will generally depend on the *quantity* of the information that the angels have about the potential ventures. Under this scenario, close-by investors have an information advantage over distant investors. It is the case because "soft" information is exclusively available to close-by investor through face-to-face interaction (Stein 2002). For example, an angel investor who has worked with an entrepreneur may come to believe that the entrepreneur is honest, prudent, and hardworking. This argument has been used in other contexts. In the banking literature, proximity between banks and companies facilitates the collection of soft information that results in a higher lending rate to close-by companies (Agarwal and Hauswald 2010). In the private equity context, an observed local bias in public pension fund investments can be explained by the fund's ability to use local connections, networks and political access to gain better information than out-of-state investors on the prospects of funds located in their home-states (Hochberg and Rauh 2012). Under this scenario, this argument suggests that there should be a negative relationship between distance and investment performance.

The objectivity effect: The quality of the venture selected will generally depend on the *quality* of the information that the investor has about the potential company. The quality of the information that angels acquire may be influenced by entrepreneurial overoptimism which has been documented in the literature. For example, Cooper et al. (1988) find that 68 percent of entrepreneurs think that the odds of their business succeeding is better than the odds for another business like theirs; only 5 percent think their odds are worse. In addition, a third of entrepreneurs believe their probability of success is 1, and 72 percent of entrepreneurs think their probability of success is at least 0.80. Russo and Schoenmaker (1992) find that managers are dramatically overconfident. In fact, Moskovitz and Vissing-Jorgensen (2002) suggest that overoptimism may be one of the reasons why an individual becomes an entrepreneur in the first place. The authors find that, after accounting for risk, entrepreneurship produces a lower return than an investment made into public market index. Furthermore, Puri and Robinson (2007) reported that overoptimism is associated with fewer work hours, stronger reference toward risky investment, and less prudent financial habits such as saving, which may have a negative impact on the company's performance and thus the investor's return. Investors could well be influenced by the entrepreneur's overoptimism, particularly during face-to-face interactions. As argued under the information effect, the number of face-to-face interaction presumably decreases in distance. If so, the influence of the entrepreneur on the investor decreases in distance. In other words, distant angels are generally better able to "objectively evaluate" a venture than local angels. The objectivity effect hence suggests that distance has a positive relationship with investment performance.

The advising effect: It is an established result in entrepreneurial finance that investors add value to the entrepreneurial companies they finance. In the context of venture capital financing, the productive input of the venture capitalist (VC) is often called "monitoring". Lerner (1995), Hellmann and Puri (2002), Kaplan and Stromberg (2004) show that VCs monitor, which can take the form of strategic advice, hiring and firing managers and founders, and establishing human resource policies, among other things. In the context of angel capital, the productive input of angels is usually called "advice". Wong et. al. (2009) also find that angel investors often invest locally. The authors suggest that a local presence allows angels to contribute easily to their investee companies. Furthermore, Harrison, Sussman and Zeira (1999) find that the value and quantity of advice reduces as distance to the investee companies increases. As effective advising becomes more costly with increasing distance, distance has a negative relationship with investment performance according to the advising effect.

The network effect: there is, however, a possible offsetting value-added effect of greater distance. While the quality of advice of investors may suffer from greater distance, these more distant investors may possibly be valuable to the companies through a form of an expanded network. Specifically, company directors and employees may already have valuable local connections, arguably making the contribution of local angels to the company's network marginal. Yet, distant investors may often bring in valuable connections that would allow the company to attract follow-on finance. This argument is based on Sorensen and Stuart's work in 2001. The authors argue that, in the venture capital context, a critical condition for companies to attract VC financing is that the VC firms must know about them. However, typical start-up companies usually fall outside the scope of the venture capital firm's activities. In the absence of public channel of information, entrepreneurs have to rely on their personal and professional network to disseminate timely and reliable information to potential investors. Because a value of network is likely to increases with distance, under this argument, distance has a positive relationship with investment performance.

Table 1 presents a summary of the effects.

3.2.2 Effects of Distance Across Categories of Angels

The data allows us to sub-categorize angel investors into three groups: (i) individual angels who invest in just one company in the entire dataset (Angel – Single); individual angels who invest in more than one company in the entire dataset (Angel – Multiple); and coalitions of angels that invest together through a fund (Angel – Fund). Subcategorizing angels may be helpful if distance can reasonably be assumed to have differential impacts among the different angel categories.

Table 1: Expected effects of greater distance on expected angel investment performance.

Performance is measured by return. Expected effects are based on prior literature reviewed in the main text. We score the expected effect of greater distance on expected return as follows: ++ (strong positive effect), + (positive effect), 0 (effect is presumably "small"), - (negative effect), -- (strong negative effect), ? (direction effect is unknown).

Effect of greater distance between angel and company	Expected Impact
Information effect	-
Objectivity effect	+
Advising effect	-
Network effect	+
Expected overall impact of greater distance on expected return	?

A stylized view on the three categories of angels is the following. First, single-company angel may be motivated to invest because of some personal connection to the company or its employees. By contrast, multiple-company angel reveals to have an interest in angel investing more broadly and may therefore exert more effort in learning about the market and advising companies. Consequently, multiple- company angels are more likely to possess greater expertise in selecting and advising companies. They will also reflect a broader network through the number of companies that they have invested in. And finally, angel groups can be expected to represent a great deal of expertise and a valuable network. This may be because they are managed by experienced, “active” angels, or because they consist of coalitions of angels who have gotten to know each other after operating in the angel market for a while.

Under this view, the single-company angel is relatively inexperienced. In an extreme case, a single-company angel is completely naïve about angel investing, in which case, he would select companies at random, provide either no advice or “white-noise” advice, and have network connections that are worth zero to the company. The information, advising, and network effects of this totally naïve single-company angel are mostly absent.

> *H1: In an extreme scenario, there is a positive relationship between distance and the return to angel investment. This relationship is mostly driven by the dominance of the objectivity effect that occurs in the selection stage.*

By contrast, I conjecture that the advising and network effect are strong for the Angel – Fund. However, the information and the objectivity effects are small or close to be absent. This conjecture rests on the fact that angel funds typically consist of coalitions of angels that can utilize its expanded network to minimize the effect of distance at the selection stage.

> *H2: The relationship between distance and the return to angel investment is mostly driven by the effects that occur in the value-added stage. The direction of the effect is depends on the relative size of the monitoring effect and the network effect.*

3.2.3 Effects of Distance Across Investors and Company’ Locations

This paper also distinguishes the effect of distance across company’s location and angel’s location. With respect to the company’s location, companies in the sample are separated into two groups: companies located in Greater Vancouver Regional District (GVRD) and companies located in the rest of BC - non-GVRD companies. This distinction is motivated by concepts of “center” and “periphery” introduced by Prebisch (1959). In his work, the author divides the world into the economic center and periphery based on the level of industrialization (economic development) of the countries. In this context, GVRD is the center due to the fact that it is the main financial and technological hub in BC. The rest of BC is viewed as the periphery.

Similarly, angels are divided into GVRD angels the rest of BC angels. The idea here is that GVRD angels possess a more valuable network than non-GVRD angels. Consequently, the network effect is stronger for companies that locate outside GVRD region than for GVRD companies. Table 2 presents the expected strengths of the network effects of distance across company’s and investor’s locations.

> *H3: Holding all other effects the same across all company-angel location pairs, the network effect must be strongest for the non-GVRD companies and GVRD investor pair. Consequently, the effect of distance on non-GVRD companies and GVRD investor pair must be less negative or more positive than the effect of distance on other company-angel location pairs.*

Table 2: The strength of network effect across company’s and investor’s locations.

Strength of the network effect ranges from 0 to +++, where +++ being the strongest.		
Company’s Location.	Investor’s Location.	
	GVRD	Non-GVRD
GVRD	0	+
Non-GVRD	+++	0

3.3 Data

3.3.1 The Venture Capital Program

The Government of British Columbia (B.C.) launched the Venture Capital Tax Incentive Program (henceforth the VCP) in 1985. The main objective of the VCP is to encourage venture capital investment and angel capital investment to provide equity capital investments to B.C. small businesses by providing 30% tax credit to eligible investments made into qualified businesses in B.C. As of today, the VCP has two distinct models that target the venture capital investment and angel capital investment: the Venture Capital Corporation (VCC) model and the Eligible Business Corporation (EBC) model.

A VCC is a registered corporation under the VCP for the sole purpose of investing funds in a number of start-up, emerging and expanding eligible small businesses. There are two types of VCCs. The first type of VCC is formally organized and managed by professional fund managers, who often receive management fee and share of the investment profits. They attract capital from members of the general public, many of whom are not accredited investors, and invest the proceeds to a number of eligible companies. In this study, we refer them as “retail VCC”. The second type of VCC, or non-retail VCC, is owned by a single or a group of accredited investors. These non-retail VCCs are not professionally managed and most importantly are authorized to raise capital from accredited investors only.

The EBC model was introduced later in 2003. It consists of tax credits for direct investments of eligible investors into an EBC. This model is administratively much simpler for angels than the VCC model since it does not require them to set up a VCC. Indeed, the EBC model was intended to reach out to a wider set of angels, including those for whom the volume of tax credits was too small to warrant the effort and costs of setting up a VCC. Eligible investors, including angels, can simply claim the 30% tax credit on the basis of an investment in an EBC.

Clearly, there are also requirements on the companies under the VCP. First, companies must be located in BC at the moment of registration. Second companies must not have more than 100 employees and pay at least 75% of the wages and salaries to BC employees. Finally, companies must operate in an eligible industry.[24]

3.3.2 Overview of the Data Sources

The data for this paper comes from a variety of sources. Our primary source is the data from the VCP described above.

What makes the VCP data special is the availability of the share registry for a substantial subset of the registered companies. This is particularly important because the share registry contains

[24] Further information on the program can be found in Hellmann and Schure (2010), Lerner et al. (2012), and on the provincial government’s website at http://www.jti.gov.bc.ca/ICP/VCP/.

detailed information about the investors and their investments. Typical information in the share registry includes investor location, investor identification, investment date, purchased price and volume. This information is particularly useful in measuring angel investment performance. In some cases, we are able to observe the history of companies' shareholders, often dating back to the date of incorporation because the registered companies that successfully attract capital are required to submit the investment records for tax credit eligibility assessment.

In addition, the BC Government requests detailed company information at the moment the companies register under the program through the registration applications. In some cases, we have their business plans. These documents enable us to learn about the registered companies on their locations, business activities, etc.

We augmented the VCP data using several additional data sources. First, we consulted several sources including ThomsonOne (VentureXpert) to learn more about the investors in our dataset, particularly their type. Investors do not only include angels and venture capitalists, but also other financial parties, corporations, and smaller groups such as societies, charitable organizations, etc. Secondly, we gathered additional data about the company's performance. The BC companies' registry and the commercial datasets of Capital IQ and SDC Global New Issues and SDC Mergers and Acquisitions) were used for data on survival of companies and possible exits (i.e. IPOs and M&As). Finally, we complemented our data through SEDAR (which contains the record of filings with the Canadian Securities Administrators of public companies and investment funds) as well as internet searches.

3.3.3 Company Dataset

I obtain the information for registered companies that received angel capital investments through the VCP program between 1999 and 2006. I choose this time frame for two reasons. First, it has a good cover pre- and post-introduction of the EBC model. Second, the 2006 cut-off allows enough time for the companies to exit.

I am able to secure systematic data for 213 companies or 62.3% of the 342 companies that falls under this sample definition. These companies are associated with 3,536 deals made by 3,352 unique investors. A deal is defined as a unique investor – investee company pair. That is all investments made by an angel into the same company are considered as one deal. This study uses deal as the unit of analysis.

I learn about the current status of the companies through a number of data sources. I use SDC Mergers and Acquisitions, SEDAR, CapitalIQ, LexisNexis and internet searches to check whether companies were involved in IPOs or acquisitions. I then use the BC and Canadian corporate registries to check for the status of the remaining companies. The corporate registries are quite reliable as companies are required to submit documentation annually. As shown in Table 3, 74% of the companies are still active, 19% of the companies have failed and the remaining 7% of the companies have exited through IPO or acquisition as of December 2012.

Our research question requires us to obtain the exit share price for the exited companies and the most recent share price for active companies[25]. For the IPO companies, share price at exit is usually clearly stated in the company's prospectus, which is available in SEDAR. For acquired companies, I use SDC, SEDAR, CapitalIQ, LexisNexis and internet search to collect the exit valuation and, more importantly, share price at exit. I am able to get exit share prices for a few acquired companies using these sources. For the remaining acquired companies, I calculate the total number of share outstanding for acquired companies using the share registry. I only include companies that have the last recorded investment date on the share registry within one year of the recorded exit date. I then divide the exit value for the computed total number of shares outstanding to get the exit share price for some acquired companies. I use internet search to get the exit share price for a few more acquired companies[26]. For failed companies, exit share price is set to zero. I use the most recent share price recorded in the share registry for active companies.

I classify the companies into industries by manually matching the company's business activity to an industry classification for innovative companies, which I based on the NAISC. For most of the companies in my sample, I obtain their business activities mainly from the business plans and registration applications. I use the internet search for the remaining companies. As shown in

[25] Having share price at exit is very important for the calculation of the angel investment return because the positive cash flow at time of exit for each individual investor is typically not available.

[26] The availability of exit share price explains the high coverage for the IPO companies and the low coverage for the acquired companies in the sample.

Panel B of Table 3, computer hardware and software industry together with the High-tech manufacturing and services industries account for almost 60% of the companies in the sample. When we group all technology-related industries together, these high-growth industries account for almost 77% of the companies in our data. 1 The other 23% of the companies in the sample is classified into tourism and other non high-tech industries. These companies are eligible under the VCP because they are also deemed to further the main objective of the VCP, namely to "enhance and diversify the provincial economy".

I divide companies into two groups: companies locate in Greater Vancouver Regional District (GVRD) including the "Lower Mainland", which is the valley extending inland from Vancouver; and companies located in the rest of BC. This distinction is motivated by division of "center" and "periphery" introduced by Prebisch (1959). In his work, the author divides the world into the economic center and periphery based on the level of industrialization (economic development) of the countries. In this context, GVRD is the center due to the fact that it is the main financial and technological hub in BC. The rest of BC is viewed as the periphery. Information on the location for a majority of the companies is taken from the business plans, the registration applications, and from other annual filings. I use internet search to find the location for the remaining companies. One concern with the company's location is that companies relocate at times. Unfortunately, I am not able to observe such event. As shown in Panel C of Table 3, the BC economy is heavily concentrated in and around the GVRD region. I find that about 71% of the companies are located in the Greater Vancouver Regional District (GVRD).

I perform a variety of checks to assess how well the sample of companies represents the population of companies that it is drawn from[27]. Panels B and C of Table 3 show that the distribution of companies in the final sample are fairly similar to the distribution of companies in the population in term of industry and location. Regarding the company's status, the final sample is biased toward active companies. In fact, the coverage of the successful companies that have gone through M&A and IPO and failed companies are roughly 40% and 45% respectively as

[27] This however does not address the question whether my sample of companies registered under the VCP program are representative to companies that would attract angel investors and venture capitalists. To do this check properly, additional data on the general population of companies is required. However, a high percentage of non-high-tech manufacturing and services companies in our sample suggests that our sample can be different. This may have a downward bias on the measure of angel capital performance as investing in non high-tech companies on average gives a lower return.

opposed to the 73.5% coverage of the active companies. The main implication for this is the measure of the angel investment performance might be slightly biased, if any, upward.

3.3.4 Angel Deal

I discuss several important properties of the angel investors and angel deals in this section.

3.3.4.1 Classification of Angels

Our population of investors is derived mainly from the companies' share registries. This population of investors do not only include angel investors, venture capitalists, but also other financial parties, corporations, and smaller groups such as societies, charitable organizations, etc.

The focus of this study requires me to separate angels from the other investors. I adopted a two-stage approach to classify the population of investors.

First, I separated the investors into two groups: humans and vehicles. Human investors are identified by their first and last name. "Vehicle investors" are the remaining ones. To ensure that no human investor is wrongly classified as a vehicle investor, we checked on all vehicle investors to see whether there was some sort of corporate designation such as "Ltd.", "Corp.", etc. in their name.

In the second stage, I performed several name-based matches with other data sources to classify the human and vehicle investors into subgroups. With respect to the human investors, it is important to distinguish angels from founders, their family, and "key employees". To do this, I matched the human investors in the share registry with the list of founders identified in the company's business plan, annual returns, and other documents and websites. I also identify non-founding managers and other key employees using the above sources. I furthermore assume investors are key employees if we observe they acquire shares at a deeply discounted price (10% or less of the maximum share price other investors pay in the same round). Finally, I score investors as family members of founders if they invest in the same company and share the same last name as founders. Naturally, such a separation cannot identify those family relationships where family members have different last names. Moreover, our methodology does not allow us to identify founders' friends, as there is no objective criterion for separating those out from angel investors. At the end of the procedure I have separated human investors into "angels" on the one hand and founders, family and key employees (henceforth "founders") on the other.

There are over 2,200 vehicle investors in our dataset. Subcategorizing them is rather an involved task because they can be of many different types of investors. I first matched the list of vehicles with the list of Venture Capital Corporations (VCCs) described in Section 3.1. [28] I classify all VCCs, except the retail VCC as angels.

I use the VC datasets of Capital IQ and ThomsonOne (VentureXpert) and internet search to learn about the remaining "vehicle investors". These vehicle investors can be angel investors, founders, corporate investors, venture capital firms and financial investors. I identify angels among the vehicle by adopting the following logic: any corporations and trusts with names that clearly reveal names of single individuals, multiple individuals, or families are angel investors.

For some of the analysis, we further subdivide the "angels" into three types, distinguishing between those who invest in one company (possibly multiple times) throughout our entire database ("Angel - Single"); those who invest in more than one company ("Angel - Multiple"); and those who co-invest using the same investment vehicle ("Angel – Fund"). Most of the vehicles in the Angel – Fund category are the VCCs where I can observe the ownership structure.

There are 3,352 angel investors made in total 3,536 deals into 213 companies in the sample. As shown in panel E of Table 4A, Angel – Single represents the largest category. They constitute for 90% of the number of angels and 86% of all angel deals. Angel – Fund is the smallest category.

3.3.4.2 Measure of Angel Investment Performance

I use the annualized internal rate of return (AIRR) as the main measure of angel investment performance in this study. This is the most commonly used measure of return by academics and practitioners (Da Rin et al. 2013). It is defined as a discount rate which makes the Net Present Value (NPV) of a stream of cash flows equal to zero. In this study, the stream of cash flow includes only an investment moment and an exit moment, both are captured by the share prices. I compute the AIRR for all angel deals in the sample. For deals that involve more than one investments, the computed AIRR is a weighted average by the investment amounts.

[28] We matched primarily on the basis of the vehicle names we find in our data. However, note that vehicle names are not necessarily similar to the names of the VC firms in Capital IQ and ThomsonOne. VC firms sometimes manage funds with quite different names. In case of uncertain matches we consulted the internet for extra information and clues. Location of the investor, which we have, was used as an additional clue.

Note that, the majority of the companies are still active as of December 2012. As a result, the computed AIRR used in this study is a combination of both the realized return (for exited companies) and the unrealized return (for active companies). I use the recorded exit share price to compute the realized return for exited companies. For companies that are still active, I use the last observed share price to compute the unrealized return.

There are two advantages with using both the realized and unrealized returns. First, it reduces the selection bias due to the fact that valuations of companies are observed only when the companies exited. These events are more frequent for either well-performing companies in case of IPOs and acquisitions or low-performing companies in case of failure, i.e. two ends of the quality spectrum (Cochrane 2005, Korteweg and Sorensen 2010). Second, it increases the sample size dramatically because exit events in private equity investment are rare (25% of companies in this sample has exited by December 2012). A large sample is essential in producing a better and more precise estimate.

Table 4B shows some interesting facts about the return to angel investment. First, the large difference between the average and the median returns seems to suggest that the return to angel investment varies quite dramatically. In fact, Figure 1 shows that almost 55% of all angel deals result in a break-even or loss and only 22% of all deals result in a positive return of 50% or more[29]. This is consistent with the results found in Mason and Harrison (2002b), Wiltbank (2005b), Wiltbank and Boeker (2007) and Riding (2008) where they find that the return to angel investment is highly skewed with more than 50% of angel investments result in negative IRR, and roughly 20% – 25% result in an IRR that exceeds 50% return.

Second, the return to angel investment varies across industries, investor’s locations and categories of angels. In term of industry, angel deals made into life science industry yields the highest return of 28% on average. This is almost double the return figure of an investment made into non High-tech industry, which, surprisingly, has the highest return among the four groups of industry. Angel investment in computer hardware and software industry seems to have the lowest return or loss at -1%.

[29] The distribution of realized return is fairly similar with roughly 62% of deals result in a loss or break-even and 25% of deals give a return of 50% or more.

With respect to investor's location, angels who locate in the GVRD region seem to outperform angels who reside outside of the GVRD region. Panel C of Table 4B reports that GVRD angels have a return that is 50% greater than the return of non-GVRD angels. This seems to be consistent with the belief that GVRD angels are on average more experienced and sophisticated due to the fact that they are exposed to a larger number of ventures than non-GVRD angels.

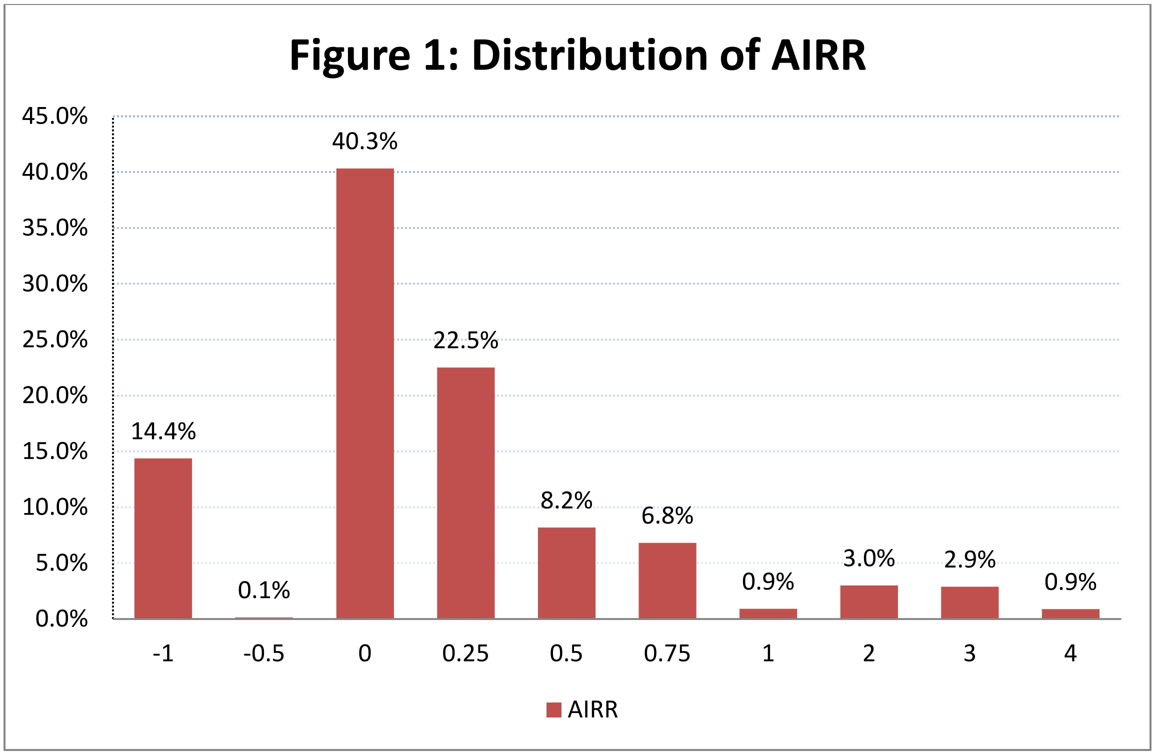
Panel E of Table 4B reports the average return across different categories of angels. On average, the Angel - Multiple category has the highest return of 18% as opposed to 10% and 6% for Angel – Single and Angel Fund categories.

I also compute the public market equivalent (PME) to provide additional insight to the return of angel investment. [30] The PME compares an angel investment with an investment of the same amount in a public market. A ratio higher than one means angel investment has returned a higher amount than a corresponding investment in the public market. In this paper, I use the TSX index and the NASDAQ index as the two benchmarks. Quarterly value of the TSX and the NASDAQ indices between 1999 and 2012 were downloaded from "Yahoo Finance" and "Google Finance". I compute the PME for all deals in the sample by discounting the exit/current share price by the quarterly return of the indices.

Table 4B shows that, on average, angel capital investment in B.C. outperformed a similar investment made into the NASDAQ index between 1999 and 2012 by a factor of 2. This is consistent with the fact that the U.S. economy experienced a recession in early and late 2000. The effect of these recessions on the Canadian economy was surprisingly mild in both cases.

Table 4B also shows that angel investment in B.C. is on par with investments made into the TSX index for the period between 1999 and 2012. This finding is consistent with Moskowitz and Jorgensen (2002). The authors find that the average return to all private equity is similar to that of the public market equity index.

[30] The calculation of the PME is for the purpose of providing a comparison between angel investments and investments made into the two popular indices. It is hard to use the PME as a performance measure in this study because an two investments made in two different period may have the same PME although one with a return of -10% and another with a return of 10%.

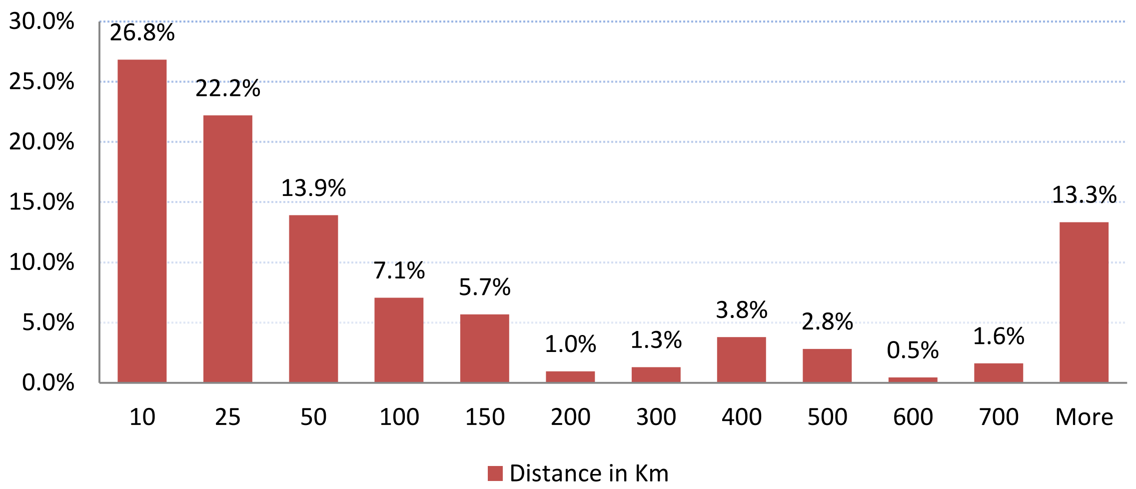


3.3.4.3 Measure of Distance

I take the following approach to compute the geographic distance for a deal – a unique investor – investee company pair. First, I collect investor's postal codes from the share registries. The postal codes allow me to divide angels into GVRD region and non – GVRD region. I then use the 2006 Postal Code Conversion File (PCCF) provided by Statistics Canada to find the longitude and latitude corresponding to all Canadian postal codes. For some Canadian postal codes that we are not able to match with the PCCF, I use a program that enables batch geocoding by sending requests to Google Maps API to retrieve the longitude and latitude. I also do this for all US zip codes to obtain their corresponding longitude and latitude. I then feed the resulting longitude and latitude pairs between an investor and his investee company(ies), to the API service of yournavigation.org, an open source routing software based on Open Street Map. yournavigation.org then returns the travel distance in kilometers of the fastest route and the travel time in second for a motor vehicle.

As shown in Table 4C, on average an investor is located almost 400km away from his investee company. The median is at around 26km, suggesting that distance is highly skewed. Figure 2 shows that this is indeed the case, with over 76% of all deals are within 150 km of the investee companies. It is also interesting that investors who invest in non high-tech industry seem to locate the furthest away from the investee companies. The reverse applies to deals made into life science and high-tech manufacturing with an average distance of about half of distance of deals made into non high-tech industry. One explanation for this may rest on the fact that investing in high-tech industries in general requires the angels to actively learn, monitor and provide more hand-on support to the entrepreneurs than investing in non high-tech industries.

Figure 2: Distribution of geographic distance between a pair of investor - company.



Moreover, deals made by Angel – Multiple and Angel - Fund categories on average have a distance of about one third of the deals made by Angel – Single. Together with the view that Angel-Single is a less experienced group of angels, this suggests the more experienced and sophisticated angels have a higher tendency to invest into close-by companies. This is consistent with the view that angels, especially more experienced and sophisticated angels, like to get involved with the company's day-to-day activities well-documented in the angel capital literature. Nevertheless, the smallest average distance is at about 130km, which almost constitutes a day trip.

In addition, GVRD investors seem to be more local investors than non-GVRD investors. This is consistent with the fact that GVRD is the main financial hub of BC where angels are exposed to a greater number ventures.

Also, as shown in panel D of Table 4C, deals that in the 50% to 75% quantile of the distance distribution (deals that have distance between 27.1 km and 124 km) are reported to have the highest return. This seems to be the first evidence of positive relationship between distance and return.

There are also some interesting observations when looking at the investor-company location pairs. As shown in Table 5, non-GVRD company and GVRD investor is the best combination with the average AIRR at around 52%. This lends further support to the fact that GVRD investors are more sophisticated in selecting and providing value-added services to the investee companies. It can also mean that non-GVRD company must overcome a huge hurdle to be able to attract GVRD investor.

Table 5 also shows that the worst combination seems to be the GVRD company and non-GVRD investor, which results in the lowest average AIRR. However, the difference in return between this location pair and the GVRD company and GVRD investor location pair is not obvious. This small difference might be due to the overall low performance of GVRD companies.

Table 6 reports the summary statistics of the variables used in the main analysis.

3.4 The Relationship Between Distance and Angel Investment Performance

This section presents empirical results of the relationship between distance and the angel investment performance. Specifically, I will first examine the overall effect of distance on an angel's annualized IRR. I will then examine whether the effect of distance varies across categories of angel investors, across investor's locations and across company's locations.

3.4.1 Overall Effect of Distance

Table 7 shows the baseline OLS regression results, where the dependent variable is the computed AIRR. Some interesting observations are shown in this table. First, GVRD companies underperform non-GVRD companies. One possible explanation for this observation is that the hurdle rate (to survive and acquire financing) for GVRD companies are much lower than for non-GVRD companies due to the availability of external financing in the GVRD region. In other words, non-GVRD companies need to show a much clearer potential than what GVRD companies need to show in order to acquire external financing from the angels. Second, the return to investment varies across different industries, with the return to investment into life science industry yielding the highest return. This higher return may be due to the higher risk associated with investments made into life science industry.

Table 8 presents the effect of distance on the return to angel investment. Columns 1 and 2 include two measures of distances: Distance km - the natural logarithm of the travel distance measured in km plus one in column 1; and distance time – the natural logarithm of the travel time measured in second plus one in column 2. Notice that I exclude the company and investor's location controls in these regressions. Columns 3 and 4 report the results with the final model specification that includes investor and company's location controls.

As shown in Table 8, the effect of distance on the return to angel investment is robust under different specifications and under different measures of distance between an angel and an investee company. Consequently, I will discuss the results shown in Columns 3 and 4.

Column 3 of Table 8 shows that there is a positive and significant relationship between distance and return. This positive relationship suggests that an increase in distance is associated with higher return for angel investments. In particular, holding all else constant, an increase in distance from the 25th percentile to the 75th percentile (or from 9.34km to 124km) increases the return to angel investment by 6 percentage points. [31,32] This suggests that the objectivity effect and the network effect outweigh the information effect and the advising effect. What this means is that an angel who is distant to a company can completely replace the information disadvantage with the ability to evaluate a company more objectively in the selection stage. It can also mean that an angel who is distant to a company can provide a different and better set of values, i.e. a different network, to the company in replacing the set of values that is only available for close-by angels, i.e. advising and hand-on supports, in the value-added stage. Of course, it can also mean

[31] In an un-tabulated result, when regressing AIRR on a distance and distance square, I find a positive coefficient for distance and a negative coefficient for distance square. This suggests that there is an inverted U-curve relationship between distance and return. That is there is a certain threshold level of distance beyond which an increase in distance reduces return.

[32] This finding is similar with Hochberg and Rauh's (2012) in the context of limited partner private equity investments. The authors find that public pension funds' performance on in-state investments is 2-4 percentage points lower than both their own similar out-of-state investments.

both. In the next section, I make an attempt to shed light on identifying the dominant effect in explaining the relationship of distance on return.

However, before that, there are a three other interesting findings that are worth discussing.

First, Columns3 and 4 of Table 8 reports that GVRD angels outperform non – GVRD angels. Specifically, angels who locate in the GVRD region, on average, have a return that is greater than the return of angels who locate outside the GVRD region by 10 percentage points. For example, if a non-GVRD angel has a return of 5%, then a GVRD angel has a return of 15%. This finding lends further support to the expectation that a GVRD angel is more experienced and sophisticated than a non-GVRD angel. This is the case because the GVRD angels are exposed to a larger number of ventures.

Second, angel investments made into GVRD companies produce a lower return. On average, an investment made into a GVRD company has a return that is lower than the return of an investment made into a non-GVRD company by almost 25 percentage points. This finding seems to suggest that not only GVRD region has a large number of ventures, but also the quality of the companies vary quite dramatically. In other words, the hurdle rate of getting financing in the GVRD region is lower than that of the non-GVRD region because of the limited availability of risk capital in non GVRD region. Consequently, lower quality companies located in the GVRD region can still acquire risk capital. This observation can also be viewed as additional support for the argument that GVRD angels are more experienced and sophisticated than non-GVRD angels. It is so because GVRD angels are not only exposed to a large number of ventures, but are also exposed to a wide range of ventures that have very different qualities.

Third, the coefficients on Angel – Multiple and Angel - Fund are positive but insignificant. Nevertheless, this provides some support for the argument that Angel – Multiple and Angel – Fund are more experienced than Angel – Simple.

3.4.2 Effect of Distance by Angel Types

As discussed in Section 4.1, the positive relationship between distance and return can be explained by the effects occurred at the selection stage and/or the effects that occurred at the value-added stage. In this section, I make an attempt to disentangle these effects.

To do this, I make use of the possibility that the effect of distance differ across different categories of angels. Specifically, the Angel – Single category is viewed as the most inexperienced and unsophisticated category of angels. In the extreme case, all the effects are close to absent with an exception of the objectivity effect. Under this scenario, there is hope to identify whether the effect of distance on return occurs at the selection stage. More importantly, under the extreme scenario, this relationship is solely driven by the objectivity effect.

Furthermore, one can assume that all the effects occurred at the selection stage are absent among the Angel – Fund category. This assumption rests on the fact that Angel Fund consists of multiple angels and has an extensive network. Consequently, Angel Fund can utilize the available human resource and extensive network in not only acquiring information but also in evaluating such information in an objective manner. If this is the case, one would then expect that the information and the objectivity effects are either (i) very small, or, in the extreme case, (ii) completely absent. If this is the case, the resulting effect of distance on return for the Angel – Fund category is mainly driven at the value-added stage.

Table 9 reports the OLS regression results under different specifications. The dependent variable is the computed AIRR and the key independent variables are the interaction terms between measures of distance and categories of angels.

As shown in Table 9, there is evidence that the effect of distance varies across different categories of angels. Specifically, at the bottom of Table 9, I report the Wald test statistic, in which I compare the coefficients of the three interaction terms. I find that distance seems to matter more for Angel – Single as opposed to Angel – Multiple. The chi square value is at 3.97 for distance km and 3.7 for distance time. Although distance does not seem to have different impacts on return between Angel – Multiple and Angel – Fund, the chi square value is at 1.88 and 1.92 for the two specifications, suggesting that the difference is fairly close to significant. In any case, there is some evidence that the effect of distance varies across different categories of angels, especially between Angel – Simple and Angel – Multiple.

Table 9 shows that distance has a positive relationship with the return for the Angel – Single category. In addition, the effect of distance on the return for Angel – Single is stronger than the effect of distance on the return for Angel – Multiple and Angel – Fund. One way to interpret these findings is as follows. The effect of distance on return for Angel – Single is mostly driven by the (positive) objectivity effect, while the effects of distance on return for Angel – Multiple and Angel – Fund are the aggregation of several effects that work in opposite direction. This seems to suggest in accordance with Hypothesis H1 that the objectivity effect plays an important role in explaining the relationship between distance and return at least for the Angel – Single category.

Regarding the Angel – Fund, Table 9 shows that there is a positive relationship between distance and the return to angel investment. However, this relationship is not statistically significant. Therefore, the dominance of the network effect occurred in the value-added stage is there but, unfortunately, not completely obvious.

Table 9 also reports two other interesting observations. First the coefficient on the interaction term between distance and Angel – Multiple is negative but insignificant. Second, the coefficient on the Angel – Multiple dummy becomes larger and significant (it is insignificant as shown in Tables 7 and 8). Together these two observations suggest that an Angel - Multiple starts with a higher return than an Angel – Simple. However, the difference in the returns for Angel – Multiple and for Angel – Simple becomes smaller as distance increases. On average, there is no significant difference in their returns as shown in Tables 7 and 8.

3.4.3 Relationship of Distance by Investor and Company's Locations

In this section, I continue the search for additional evidence that would shed light on whether the relationship between distance and return are driven at the selection stage or at the value-added stage. To do this, I decompose the angels and the companies by their locations.

As discussed in Section 2, the relationship between distance and return can be different across companies located in the center and companies located in the periphery. In particular, the network effect should be larger for non-GVRD companies than for GVRD companies. This is the case because the GVRD angels, who are the distant investors to the non-GVRD companies, have more valuable networks.

To examine this, I adopt two different approaches: (i) the investor-company location dummy approach and (ii) the interaction term between distance and location approach.

Regarding the first approach, I construct four investor-company location dummies: GVRD Company and GVRD Angel dummy, GVRD Company and non-GVRD Angel dummy, non-GVRD Company and GVRD Angel dummy, and non-GVRD Company and non-GVRD Angel dummy. Table 10 regresses the AIRR on these dummies and the controls. The GVRD Company and non-GVRD Angel dummy is purposely omitted so that the network effect can be picked up by examining the coefficient on the non-GVRD Company and GVRD Angel dummy.

As shown in Table 10, the investment return for the non-GVRD Company and GVRD Angel pair is significantly greater than the return to the GVRD Company and non-GVRD Angel pair. Indeed, the Wald test shown at the bottom of Table 9 shows that this investor-company location pair has the greatest return in comparison to all other location pairs. Although this can be viewed this as an evidence supporting the dominance of the network effect, this could mainly be driven by the fact that GVRD companies do poorly in general. Note that, company and investor location controls are not included in this regression due to multicollinearity problem.

Regarding the second approach, I construct interactions term between distance and company location dummies, and between distance and investor location dummies. Table 11 shows the OLS regression result for this approach.

If the network effect is the main determinant of the relationship between distance and the return to angel investment, one should expect to see that distance matters more for non-GVRD companies. In particular, the coefficient on the interaction term between distance and non-GVRD companies should be greater in value than the coefficient on the interaction term between distance and GVRD companyies holding all other effects the same across the two groups of companies.

Columns 1 and 2 of Table 11 show the reverse. Only the coefficient on the interaction term between distance and GVRD companies is positive and statistically significant. More importantly, it is greater in value than the coefficient on the interaction term between distance and non-GVRD companies. This result suggests that the network effects that occurred at the value-added stage cannot explain the positive relationship between distance and return to angel investment found in previous sections.

In fact, the positive and significant effect of distance on the interaction term between distance and GVRD companies provides further support for the dominance of the objectivity effect. This is the case because non-GVRD angels, distant angel investors to GVRD companies, are less experienced and their networks are not valuable. As a result, the objectivity effect is the most obvious among the four effects for the non-GVRD angels. Thus, the positive relationship found in column 1 and 2 of Table 11 should be mainly driven by the objectivity effect.

In the search for further evidence of the objectivity effect, I decompose the angels (instead of companies) by their locations. As mentioned above, non-GVRD angels are less experienced. If this is the case, the objectivity effect should prevail and the coefficient of the interaction term between distance and non-GVRD investors must be positive. This is indeed what I find. Also, the fact that the coefficient of the interaction term between distance and non-GVRD investors is greater than the coefficient of the interaction term between distance and GVRD investors suggests a dominance of the objectivity effect.

Finally, The Wald test reported at the bottom of Table 11 shows that there is a significant difference between the effect of distance on return for investments made into GVRD companies and investments made into non-GVRD companies. The chi square values for the distance in km and distance in time are 10.47 and 9.5 respectively.

3.5 Conclusion

The effect of distance on the return to angel investment can be explained by four distinct effects: the information effect and the objectivity effect at the selection stage; the advising effect and the network effect at the value-added stage.

Using a unique dataset that contains detailed information on angel investments and the locations of the angels and the companies, this paper reports several interesting results. First there is a positive relationship between distance and angel investment performance, measured by the annualized internal rate of return. In particular, holding all else constant, an increase in distance from the 25th percentile to the 75th percentile increases the return to angel investment by 6 percentage points. Second, the effect of distance varies across different categories of angels. Specifically, this study shows that distance matters more to the less experienced angels, who invest in only one company in the entire dataset. Third, this paper finds that distance matters more to companies locating in a center, which suggests that the relationship between distance and return seems to be determined mostly at the selection stage. Finally, this paper documents that the return to angel investment is highly skewed with 55% of all angel deals resulting in a break-even or loss and only 22% of all deals result in a positive return of 50% or more.

One should be careful in interpreting these results due to endogeneity issue. Endogeneity enters into our analysis through two main channels. First, the entrepreneur may strategically choose the optimal location that allows him the best access to the angel capital market. This decision may be based on unobservable company and entrepreneur characteristics. Second, even if the company's location choice is exogenous, a match between an angel and a company is still endogenous. This paper takes an alternative approach to distinguish the selection effect from the treatment effect. Observing the possibility that the selection and treatment effects can be different across different type of angel investors and also across different company's location, this paper makes use of the richness of the data to separate out the selection effect from the treatment effect.

This paper is the first systematic study that analyzes the importance of distance on the performance of angel investments. The findings are of importance for policy makers interested in designing policies to encourage angel investment, and for angels when making the investment decision. Hopefully this paper encourages academics to seriously (re)consider the role of geography in the angel capital market.

Table 3: Properties of companies - sample vs. population.

This table compares our sample of companies to the overall population of companies that received angel investments through the VCP program between 1999 and 2006. Panel A presents the distribution of companies by company's status. Panel B presents the distribution of companies by company's industries. Panel C presents the distribution of companies by company's locations. Variables are defined in Table A1.

Panel A: Distribution of companies by company's status.

Status	Final Sample		Population	
	# Companies	**%**	**# Companies**	**%**
Acquired	10	4.7%	30	8.8%
IPO	4	1.9%	5	1.5%
Failed	41	19.2%	92	26.9%
Active	158	74.2%	215	62.9%
Total	**213**	**100.0%**	**342**	**100.0%**

Panel B: Distribution of companies by company's industries.

Industries	Final Sample		Population	
	# Companies	**%**	**# Companies**	**%**
Non High-tech Others	50	23.5%	86	25.1%
Life Science	37	17.4%	57	16.7%
Computer Hardware and Software	83	39.0%	115	33.6%
High-tech Manufacturing & Services	43	20.2%	84	24.6%
Total	**213**	**100.0%**	**342**	**100%**

Panel C: Distribution of companies by company's locations.

Locations	Final Sample		Population	
	# Companies	**%**	**# Companies**	**%**
GVRD	152	71.4%	228	66.7%
Non -- GVRD	61	28.6%	114	33.3%
Total	**213**	**100.0%**	**342**	**100.0%**

Table 4A: Properties of angel deals - Overall Distributions.

This table reports the properties of angel deals included in the final sample of companies that received angel investments through the VCP program between 1999 and 2006. Panel A presents the properties of angel deals by company's status. Panel B presents the properties of angel deals by company's industries. Panel C presents the properties of angel deals by investor's locations. Panel D presents the properties of angel deals by the geographic proximity between an angel and an investee company. Panel E presents the properties of angel deals by angel investor's categories.

Panel A: Summary statistics of angel deals by company's status.

Status	Investors		Deals	
	Numbers	%	Numbers	%
Acquired	359	10%	364	10%
IPO	123	4%	126	4%
Failed	475	14%	480	14%
Active	2464	72%	2566	73%
All	3421	100%	3536	100%

Panel B: Summary statistics of angel deals by company's industries.

Industry	Investors		Deals	
	Numbers	%	Numbers	%
Non hi-tech other	624	18%	635	18%
Life science	941	27%	968	27%
Computer hardware and software	1159	34%	1210	34%
Hi-tech manufacturing & services	702	20%	723	20%
All	3426	100%	3536	100%

Panel C: Summary statistics of angel deals by angel investor's locations.

Location	Investors		Deals	
	Numbers	%	Numbers	%
GVRD	2058	61%	2213	63%
Non – GVRD	1294	39%	1323	37%
All	3352	100%	3536	100%

Panel D: Summary statistics of angel deals by angel investor's geographic proximity to the investee companies.

Geographic Proximity (km)	Investors		Deals	
	Numbers	%	Numbers	%
First 25% Quantile (< 9.34)	839	25%	887	25%
25% - 50% Quantile (9.34 - 27.1)	867	25%	898	25%
50% - 75% Quantile (27.1 - 124)	807	24%	836	24%
Last 25% Quantile (> 124)	903	26%	915	26%
All	3416	100%	3536	100%

Panel E: Summary statistics of angel deals by angel investor's categories.

Category	Investors		Deals	
	Numbers	%	Numbers	%
Angel - Single	3031	90%	3031	86%
Angel - Multiple	249	7%	377	11%
Angel - Fund	72	2%	128	4%
All	3352	100%	3536	100%

Table 4B: Properties of angel deals - Investment and return.

This table reports the properties of angel deals included in the final sample of companies that received angel investments through the VCP program between 1999 and 2006. Panel A presents the properties of angel deals by company's status. Panel B presents the properties of angel deals by company's industries. Panel C presents the properties of angel deals by investor's locations. Panel D presents the properties of angel deals by the geographic proximity between an angel and an investee company. Panel E presents the properties of angel deals by angel investor's categories.

Panel A: Summary statistics of angel deals by company's status.

Status	Invt. Amt (CAD)		Annualized IRR		PME - TSX		PME - NASDAQ	
	Average	Median	Average	Median	Average	Median	Average	Median
Acquired	38235	20000	55%	39%	2.42	1.56	3.31	2.73
IPO	58967	15000	97%	15%	1.59	1.29	1.39	0.89
Failed	28782	10000	-100%	-100%	0.00	0.00	0.00	0.00
Active	36268	13750	22%	0%	1.00	0.84	2.70	2.30
All	36338	12525	10%	0%	1.02	0.78	2.35	2.07

Panel B: Summary statistics of angel deals by company's industries.

Industry	Invt. Amt (CAD)		Annualized IRR		PME - TSX		PME - NASDAQ	
	Average	Median	Average	Median	Average	Median	Average	Median
Non hi-tech other	42593	10034	14%	0%	1.30	0.84	2.92	2.20
Life science	28781	12000	28%	0%	1.02	0.85	2.64	2.47
Computer hardware and software	39833	15000	-1%	0%	0.86	0.86	1.93	1.86
Hi-tech manufacturing & services	35231	15000	3%	0%	1.06	0.85	2.28	2.04
All	36338	12525	10%	0%	1.02	0.78	2.35	2.07

Panel C: Summary statistics of angel deals by angel investor's locations.

Location	Invt. Amt (CAD)		Annualized IRR		PME - TSX		PME - NASDAQ	
	Average	Median	Average	Median	Average	Median	Average	Median
GVRD	38675	15000	12%	0%	0.99	0.77	2.30	2.11
Non - GVRD	32439	12000	8%	0%	1.09	0.83	2.44	2.04
All	36338	12525	10%	0%	1.02	0.78	2.35	2.07

Table 4B (continued)

Panel D: Summary statistics of angel deals by angel investor's geographic proximity to the investee companies.

Geographic Proximity (km)	**Invt. Amt (CAD)**		**Annualized IRR**		**PME - TSX**		**PME - NASDAQ**	
	Average	**Median**	**Average**	**Median**	**Average**	**Median**	**Average**	**Median**
First 25% Quantile (< 9.34)	39145	12500	7%	0%	0.94	0.73	2.24	2.04
25% - 50% Quantile (9.34 - 27.1)	30988	12500	7%	0%	0.97	0.78	2.23	1.93
50% - 75% Quantile (27.1 - 124)	32937	12500	20%	0%	1.03	0.84	2.39	2.18
Last 25% Quantile (> 124)	41976	15000	8%	0%	1.14	0.84	2.54	2.04
All	36338	12525	10%	0%	1.02	0.78	2.35	2.07

Panel E: Summary statistics of angel deals by angel investor's categories.

Category	**Invt. Amt (CAD)**		**Annualized IRR**		**PME - TSX**		**PME - NASDAQ**	
	Average	**Median**	**Average**	**Median**	**Average**	**Median**	**Average**	**Median**
Angel - Single	27427	11166	10%	0%	1.01	0.77	2.35	2.06
Angel - Multiple	51325	25000	18%	0%	1.12	0.97	2.39	2.12
Angel - Fund	200000	86597	6%	0%	1.04	0.83	2.21	2.15
All	36338	12525	10%	0%	1.02	0.78	2.35	2.07

Table 4C: Properties of angel deals - Distance.

This table reports the properties of angel deals included in the final sample of companies that received angel investments through the VCP program between 1999 and 2006. Panel A presents the properties of angel deals by company's status. Panel B presents the properties of angel deals by company's industries. Panel C presents the properties of angel deals by investor's locations. Panel D presents the properties of angel deals by the geographic proximity between an angel and an investee company. Panel E presents the properties of angel deals by angel investor's categories.

Panel A: Summary statistics of angel deals by company's status.

Status	Distance Km		Distance Time	
	Average	Median	Average	Median
Acquired	798	28	25781	912
IPO	477	116	15581	3807
Failed	347	19	11244	640
Active	348	26	11274	851
All	399	26	12917	872

Panel B: Summary statistics of angel deals by company's industries.

Industry	Distance Km		Distance Time	
	Average	Median	Average	Median
Non hi-tech other	596	78	19384	2555
Life science	296	19	9475	630
Computer hardware and software	440	17	14258	553
Hi-tech manufacturing & services	295	36	9600	1176
All	399	26	12917	872

Panel C: Summary statistics of angel deals by angel investor's locations.

Location	Distance Km		Distance Time	
	Average	Median	Average	Median
GVRD	64	16	2099	538
Non - GVRD	959	207	31012	6791
All	399	26	12917	872

Panel D: Summary statistics of angel deals by angel investor's geographic proximity to the investee companies.

Geographic Proximity (km)	Distance Km		Distance Time	
	Average	Median	Average	Median
First 25% Quantile (< 9.34)	5	4	149	142
25% - 50% Quantile (9.34 - 27.1)	16	15	521	497
50% - 75% Quantile (27.1 - 124)	62	48	2013	1578
Last 25% Quantile (> 124)	1466	738	47422	24050
All	399	26	12917	872

Panel E: Summary statistics of angel deals by angel investor's categories.

Category	Distance Km		Distance Time	
	Average	Median	Average	Median
Angel - Single	443	29	14337	945
Angel - Multiple	129	16	4202	528
Angel - Fund	153	15	4970	480
All	399	26	12917	872

Table 5: Average and median AIRR for each investor-company location pairs.
This table reports the average and the median AIRR for four distinct investor-company location pairs. Variables are defined in Table A1.

Company's Location	Investor's Location			
	GVRD		Non-GVRD	
	Average	Median	Average	Median
GVRD	4.7%	0.0%	4.3%	0.0%
Non-GVRD	52.3%	5.2%	14.2%	0.0%

Table 6: Descriptive statistics.
This table provides descriptive statistics for all dependent and independent variables. Variables are defined in Table A1. For dummy variables the Mean column reports the frequency of observations, and the 25%, Median, and 75% are omitted.

Variable	# Obs	Min	25%	Median	Mean	75%	Max	S.D.
AIRR	3536	-100%	-8%	0%	10%	21%	630%	83%
Distance km	3536	0.02	9	26	399	122	5482	991
Distance time	3536	0.00	304	872	12917	3997	140000	31910
Angel - Single	3536	0.00	-	-	0.85	-	1.00	0.35
Angel - Multiple	3536	0.00	-	-	0.11	-	1.00	0.31
Angel - Fund	3536	0.00	-	-	0.04	-	1.00	0.19
GVRD - Company	3536	0.00	-	-	0.78	-	1.00	0.42
GVRD - Angel	3536	0.00	-	-	0.63	-	1.00	0.48
Non High-tech Manufacturing and Services	3536	0.00	-	-	0.18	-	1.00	0.38
Life Science	3536	0.00	-	-	0.27	-	1.00	0.44
Computer Hardware and Software	3536	0.00	-	-	0.34	-	1.00	0.47
High-tech Manufacturing and Services	3536	0.00	-	-	0.20	-	1.00	0.40

Table 7: Baseline Specification.

This table reports results from OLS regressions. The unit of analysis is at deal level. Dependent variable is AIRR. Independent variables are GVRD - COMPANY, GVRD - ANGEL, ANGEL - MULTIPLE, and ANGEL - FUND, and INDUSTRY dummies. The unreported control variables are age, capital-raised, and calendar time. All variables are defined in Table A1. Heteroskedasticity-robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Independent variables	1
GVRD - Company	-0.250***
	(0.0387)
GVRD - Angel	0.0437
	(0.0303)
Angel - Multiple	0.0462
	(0.0492)
Angel - Fund	0.0392
	(0.0753)
Life Science	0.125**
	(0.0529)
Computer Hardware & Software	-0.0704
	(0.0476)
High-tech Manufacturing & Services	-0.0887*
	(0.0489)
Controls	YES
Constant	0.0701
	(0.180)
Observations	3,536
Number of companies	213
R-squared	0.142

Table 8: The Relationship between Distance and Angel Investment Performance.
This table reports results from OLS regressions. The unit of analysis is at deal level. Dependent variable is AIRR. Independent variables are DISTANCE - KM, DISTANCE - TIME, GVRD - COMPANY, GVRD - ANGEL, ANGEL - MULTIPLE, and ANGEL - FUND, and INDUSTRY dummies. The unreported control variables are age, capital-raised, and calendar time. All variables are defined in Table A1. Heteroskedasticity-robust standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Independent variables	2	3	4	5
Distance - Km	0.0203***		0.0263***	
	(0.00666)		(0.00799)	
Distance - Time		0.0185***		0.0237***
		(0.00618)		(0.00728)
GVRD - Company			-0.247***	-0.248***
			(0.0386)	(0.0386)
GVRD - Angel			0.0965***	0.0923**
			(0.0365)	(0.0359)
Angel - Multiple	0.0766	0.0758	0.0546	0.0540
	(0.0486)	(0.0486)	(0.0495)	(0.0494)
Angel - Fund	0.0480	0.0496	0.0441	0.0471
	(0.0736)	(0.0736)	(0.0750)	(0.0751)
Life Science	0.120**	0.119**	0.139***	0.138***
	(0.0507)	(0.0507)	(0.0524)	(0.0524)
Computer Hardware & Software	-0.0931**	-0.0936**	-0.0570	-0.0569
	(0.0466)	(0.0467)	(0.0481)	(0.0482)
High-tech Manufacturing & Services	-0.0698	-0.0712	-0.0789	-0.0801
	(0.0488)	(0.0488)	(0.0487)	(0.0487)
Controls	YES	YES	YES	YES
Constant	-0.0675	-0.119	-0.0135	-0.0801
	(0.186)	(0.191)	(0.188)	(0.193)
Observations	3,536	3,536	3,536	3,536
Number of companies	213	213	213	213
R-squared	0.133	0.132	0.145	0.145

Table 9: The Relationship between Distance and Angel Investment Performance - Decomposition of Angel Investors.

This table reports results from OLS regressions. The unit of analysis is at deal level. The dependent variable is AIRR. Independent variables are SINGLE * KM, MULTIPLE * KM, FUND * KM, SINGLE * TIME, MULTIPLE * TIME, FUND * TIME, GVRD - COMPANY, GVRD - ANGEL, ANGEL - MULTIPLE, and ANGEL - FUND. The unreported control variables are age, capital-raised, industry dummies and calendar time. All variables are defined in Table A1. Heteroskedasticity-robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Independent variables	2	3	4	5
Single * Km	0.0227***		0.0303***	
	(0.00692)		(0.00816)	
Multiple * Km	-0.0201		-0.0276	
	(0.0280)		(0.0288)	
Fund * Km	0.0330		0.0324	
	(0.0332)		(0.0337)	
Single * TIME		0.0205***		0.0273***
		(0.00646)		(0.00750)
Multiple * TIME		-0.0170		-0.0237
		(0.0254)		(0.0262)
Fund * TIME		0.0307		0.0296
		(0.0283)		(0.0287)
GVRD - Company			-0.251***	-0.252***
			(0.0387)	(0.0387)
GVRD - Angel			0.101***	0.0964***
			(0.0364)	(0.0358)
Angel - Multiple	0.216**	0.324*	0.242**	0.392**
	(0.0994)	(0.173)	(0.0996)	(0.175)
Angel - Fund	0.0195	-0.0110	0.0409	0.0364
	(0.110)	(0.179)	(0.111)	(0.180)
Controls	YES	YES	YES	YES
Constant	-0.0788	-0.134	-0.0312	-0.107
	(0.185)	(0.190)	(0.188)	(0.193)
Distance * Single vs. Multiple	0.0428	0.0375	0.0579**	0.051*
	(2.21)	(2.06)	(3.97)	(3.70)
Distance * Single vs. Fund	-0.0103	-0.0102	-0.0021	-0.0023
	(0.09)	(0.13)	(0.00)	(0.01)
Distance * Multiple vs. Fund	-0.0531	-0.0477	-0.06	-0.0533
	(1.51)	(1.58)	(1.88)	(1.92)
Observations	3,536	3,536	3,536	3,536
Number of companies	213	213	213	213
R-squared	0.133	0.133	0.146	0.146

Table 10: The Relationship between Distance and Angel Investment Performance: Location Dummy Approach.

This table reports results from OLS regressions. The unit of analysis is at deal level. The dependent variable is AIRR. Independent variables are investor-company location dummies. The omitted dummy is the GVRD Company - non-GVRD Angel. The unreported control variables are age, capital-raised, industry dummies and calendar time. All variables are defined in Table 4. Heteroskedasticity-robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1
GVRD Com - GVRD Angel	-0.0466
	(0.0331)
Non-GVRD Com - GVRD Angel	0.402***
	(0.0597)
Non-GVRD Com - non-GVRD Angel	0.0897*
	(0.0485)
Angel - Multiple	0.0498
	(0.0497)
Angel - Group	0.00393
	(0.0727)
Controls	YES
Constant	-0.0837
	(0.121)
GVRD Com - GVRD Angel vs. Non-GVRD Com - GVRD Angel	-0.449***
	(58.98)
GVRD Com - GVRD Angel vs. Non-GVRD Com - Non-GVRD Angel	-0.136***
	(8.11)
Non-GVRD Com - GVRD Angel vs. Non-GVRD Com - Non-GVRD Angel	0.323
	(21.18)
Observations	3,536
Number of companies	213
R-squared	0.138

Table 11: The Relationship between Distance and Angel Investment Performance: Interactions with Distance Approach.

This table reports results from OLS regressions. The unit of analysis is at deal level. The dependent variable is AIRR. Independent variables are GVRD - INVT * KM, NON - GVRD - INVT * KM, GVRD - INVT * TIME, NON - GVRD - INVT * TIME, GVRD - COM, GVRD - INVT, MULTIPLE - COM - ANGEL, ANGEL - FUND, GVRD - COM * KM, NON - GVRD - COM * KM, GVRD - COM * TIME, and NON - GVRD - COM * TIME, GVRD - COMPANY, GVRD - ANGEL, ANGEL - MULTIPLE, and ANGEL - FUND. The unreported control variables are age, capital-raised, industry dummies and calendar time. All variables are defined in Table A1. Heteroskedasticity-robust standard errors are reported in the parentheses. Chi-square values at one degree of freedom are reported in the parentheses for all hypothesis testing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4
GVRD - Com * Km	0.0426***			
	(0.00921)			
Non - GVRD - Com * Km	-0.0186			
	(0.0165)			
GVRD - Com * Time		0.0385***		
		(0.00845)		
Non - GVRD - Com * Time		-0.0136		
		(0.0146)		
GVRD - Invt * Km			0.0141	
			(0.0144)	
Non - GVRD - Invt * Km			0.033***	
			(0.00977)	
GVRD - Invt * Time				0.0130
				(0.0121)
Non - GVRD - Invt * Time				0.0302***
				(0.00922)
GVRD – Company	-0.504***	-0.642***	-0.255***	-0.256***
	(0.0907)	(0.136)	(0.0400)	(0.0399)
GVRD - Angel	0.124***	0.119***	0.169**	0.219*
	(0.0391)	(0.0385)	(0.0752)	(0.116)
Angel – Multiple	0.0565	0.0560	0.0558	0.0552
	(0.0494)	(0.0494)	(0.0494)	(0.0494)
Angel – Fund	0.0525	0.0558	0.0422	0.0444
	(0.0753)	(0.0755)	(0.0752)	(0.0754)
Controls	YES	YES	YES	YES
Constant	0.131	0.164	-0.0325	-0.122
	(0.197)	(0.211)	(0.189)	(0.196)
Distance * GVRD - Com vs. Non - GVRD - Com	0.0612***	0.0521***		
	(10.47)	(9.50)		
Distance * GVRD - Invt vs. Non - GVRD - Invt			-0.0187	-0.0172
			(1.13)	(1.26)
Observations	3,536	3,536	3,536	3,536
Number of companies	213	213	213	213
R-squared	0.149	0.148	0.145	0.145

Table A1: Variable definitions.

Variable	Description
(a) Dependent variables	
AIRR	the annualized internal rate of return for an angel deal. In case of multiple investment deals, this variable is the weighted average of the annualized internal rate of return for all investments of the same deal by the investment amounts.
(b) Independent variables	
DISTANCE-KM	natural logarithm of one plus the actual travel distance between an angel investor and the corresponding investee company measured in kilometer.
DISTANCE-TIME	natural logarithm of one plus the actual travel time between an angel investor and the corresponding investee company measured in seconds
ANGEL - SINGLE	dummy variable that takes on value of 1 if an investor or an investment vehicle invests in only one companies; 0 otherwise.
ANGEL - MULTIPLE	dummy variable that takes on value of 1 if an investor or an investment vehicle invests in more than one company; 0 otherwise.
ANGEL - FUND	dummy variable that takes on value of 1 if an investment vehicle is owned by more than one angel investors; 0 otherwise.
GVRD - COMPANY	dummy variable that takes on value of 1 if the company is located in the Greater Vancouver region; 0 otherwise.
GVRD - ANGEL	dummy variable that takes on value of 1 if the angel investor is located in the Greater Vancouver region; 0 otherwise.
(c) Interaction terms	
SINGLE - KM	interaction between single - company - angel dummy and the natural logarithm of 1 plus the actual travel distance between an angel investor and the corresponding investee company measured in km.
MULTIPLE - KM	interaction between multiple - company - angel dummy and the natural logarithm of 1 plus the actual travel distance between an angel investor and the corresponding investee company measured in km.
FUND - KM	interaction between angel – fund dummy and the natural logarithm of 1 plus the actual travel distance between an angel investor and the corresponding investee company measured in km.
SINGLE - TIME	interaction between single - company - angel dummy and the natural logarithm of 1 plus the actual travel time between an angel investor and the corresponding investee company measured in second.

MULTIPLE - TIME	interaction between multiple - company - angel dummy and the natural logarithm of 1 plus the actual travel time between an angel investor and the corresponding investee company measured in second.

Table A1 (continued)

FUND - TIME	interaction between angel – fund dummy and the natural logarithm of 1 plus the actual travel time between an angel investor and the corresponding investee company measured in second.
GVRD - COM * KM	interaction between GVRD company dummy and the natural logarithm of 1 plus the actual travel distance between an angel investor and the corresponding investee company measured in km.
NON - GVRD - COM * KM	interaction between one minus GVRD company dummy and the natural logarithm of 1 plus the actual travel distance between an angel investor and the corresponding investee company measured in km.
GVRD - COM * TIME	interaction between GVRD company dummy and the natural logarithm of 1 plus the actual travel time between an angel investor and the corresponding investee company measured in second.
NON - GVRD - COM * TIME	interaction between one minus GVRD company dummy and the natural logarithm of 1 plus the actual travel time between an angel investor and the corresponding investee company measured in second.
GVRD - INVT * KM	interaction between GVRD investor dummy and the natural logarithm of 1 plus the actual travel distance between an angel investor and the corresponding investee company measured in km.
NON - GVRD - INVT * KM	interaction between one minus GVRD investor dummy and the natural logarithm of 1 plus the actual travel distance between an angel investor and the corresponding investee company measured in km.
GVRD - INVT * TIME	interaction between GVRD investor dummy and the natural logarithm of 1 plus the actual travel time between an angel investor and the corresponding investee company measured in second.
NON - GVRD - INVT * TIME	interaction between one minus GVRD investor dummy and the natural logarithm of 1 plus the actual travel time between an angel investor and the corresponding investee company measured in second.

(d) Control variables	
AGE	natural logarithm of one plus the company age at time of investment measured in quarters. In case of multiple investment deals, company age is measured at time of the earliest investment.
CAPITAL-RAISED	natural logarithm of one plus the amount of cumulative capital raised at time of investment measured in CAD. In case of multiple investment deals, capital raised is measured at time of the earliest investment.
INDUSTRY	set of mutually exclusive dummy variables that take the value 1 if the company is reported to operate in one of the following industries; 0 otherwise. Our data gives the following options: *Life science; Computer hardware & software; High-tech manufacturing and services; Non High-tech others.*

Chapter 4: Hiding as a Screening Device: Understanding the Angel Capital Market

4.1 Introduction

> *"...the search is also extremely inconvenient for the seller, entrepreneur, because angel investors prize their privacy. For good reason, they make themselves extremely difficult to find. The entrepreneur has a difficult time indeed locating investors with discretionary net worth, the inclination to subject themselves to the high levels of risk associated with this type of investment and the skills necessary to evaluate and add value to these ventures."*
>
> Benjamin and Margulis (2001 p. 15)

It is well documented that the venture capitalists focus on later-stage ventures. According to 2013Q1 Venture Capital Monitor, a quarterly report on the Canadian venture capital investment conducted by Industry Canada, venture capitalists invest 14 times as much in later-stage companies than in seed and start-up companies. (Industry Canada 2013). That leaves a large number of “high-technology” start-up ventures arduously searching for risk capital in the angel capital market, the market for risk capital supplied by arms-length individual financiers. However, as shown in the opening quote: "For good reason they [angels] make themselves extremely difficult to find". In fact, studies of the angel capital market often distinguish between a visible and hidden segment of the angel capital market. According to the 2011 OECD report, the visible segments of the angel capital market in the US and in Canada are approximately $469 Million and $34 Million, respectively, representing, so the report claims, only 3 and 9 percent, respectively, of the total size of the angel capital market in the US and in Canada.

Why do angels hide? According to Van Osnabrugge and Robinson (2000), angels would be swamped with hundreds of project proposals were information about them widely available. But is avoiding to be “swamped” the reason for angels to hide? It seems that the fit between the angels and companies she funds becomes better if the angel can select from many, rather than a few project proposals. In this paper, we introduce a model to explore whether and when angels deliberately hide from entrepreneurs. In the model angels may choose to hide to screen out low-productivity entrepreneurs.

Entrepreneurs seeking angels in the venture capital market appears to be a classic search story. There are scattered agents on both sides of the market who do not know much about each other. However, as the literature indicates, the search problem in the angel capital market does not spring from the standard spatial, information and coordination impediments. Rather angels face a market that is too "thick" and would rather face fewer and higher productivity entrepreneurs. Angels erect additional barriers to matching, giving the appearance of a classic search environment. The additional barriers effectively induce greater search by entrepreneurs.

Is forcing greater search by entrepreneurs the best screening mechanism? In contrast to angel investors, venture capitalists are typically well-known entities in the venture capital market. Venture capitalists are usually distinguished from angels as having greater funds as well as a greater flexibility to take on and support different types of projects. They usually take on quite a few projects whereas angels usually only take on less than a handful projects at a time (Van Osnabrugge and Robinson 2000). Sometimes an entrepreneur first secures an angel investor and then, if the project is successful, subsequently both the angel and entrepreneur approach a venture capitalist to grow the business. There have been efforts to form angel consortiums and networks to screen and direct entrepreneurs (Wong, 2010). In fact, a formal group of angels sometimes form a venture capital firm. However, these alternative structures are not the norm, even though they are often supported by governments. The fact that the angel capital market is as large as the venture capital market and contains many lone angels suggests that this structure fills an important role.[33] Also, the fact that these lone angels choose to hide and force greater search on entrepreneurs suggest that hiding is a proven strategy.

In this paper, we develop a theoretical model of hide and seek search. Unlike the traditional search models, there are no natural impediments to angels seeking an entrepreneur. If angels do not hide, they can encounter entrepreneurs with certainty. Thus, the main feature of our model is that search frictions, if any, arise from *choice* (by angels), rather than technology.

Hiding is relevant in our model because there are low and high-productivity entrepreneurs. Angels would prefer to match with high-productivity entrepreneurs, but cannot identify them prior to matching and forming a firm. Hiding provides a way to screen entrepreneurs because it discourages entrepreneurs from searching. Specifically, angels could choose to hide sufficiently hard (being appropriately elusive) to discourage low-productivity entrepreneurs, while high-productivity entrepreneurs would still find it worthwhile to incur the costs of search. Interestingly, social surplus is often increased when angels choose to hide, though in some circumstances surplus may fall.

The explicit model we develop involves a matching function, similar to Pissarides (2000), except that the default of not hiding involves angels matching with probability 1. For generality, we have developed the model where there are a continuum of angels. We make assumptions that result in all angels being active and we normalize their number to 1. The choice of the hiding intensity then is a collective decision for angels. However, we could also interpret the model as having only one angel, in which case the choice of hiding intensity is an individual decision. This later interpretation is consistent with the angel capital market being highly heterogeneous.

[33] Angel investing is an important source of funds for entrepreneurs. Riding (2008) finds that there are about 15,800 angels investing at least $1.9 billion annually in the entrepreneurial firms in Canada. In contrast, venture capital firms invest less than half that amount, at about $870 million annually. See Shane (2008) for similar information on the US Angel Capital Market. Madill, Haines, and Riding (2005) note that business angel investors not only constitute an important source of financing, they also provide significant non-financial inputs to the growth and viability of the firms through, among other things, mentoring their industry experience and contacts. In this paper, we abstract from the other roles angel investors might play in start-up firms.

Whereas our analysis is motivated and framed in terms of the angel capital market, we believe it applies more broadly. Interestingly, the origin of the term "angel" refers to well-heeled individuals who financed Broadway theatre productions in the beginning of the 20th century.[34] Like the angel capital market, the entertainment financing market seems to be characterized by reclusive financers trying to hide from large numbers of people with ideas of variable quality. Indeed, the theme of a number of movies is about the obstacles placed in front of writers trying to find an agent to promote their work as plays and movies.[35] Similarly, in the labour market the common practice of not postings jobs, but rather letting workers search for jobs has a hide and seek aspect.

The paper proceeds as follows. Section 2 describes the angel capital market and provides details on entrepreneurs and the angels. Section 3 examines the angel and entrepreneurs' optimization problems and market equilibrium. The efficiency of the angel capital market is examined in Section 4. Section 5 summarizes the results of the model and discusses a way to generalize of the analysis.

[34] See e.g. Benjamin and Margulis (2001). However Wetzel (1983) was a pioneer in employing the term "angel" to describe individuals who provide their own capital to support entrepreneurial ventures.

[35] Some movies include *The Lonely Lady*, *The Player*, *French Exit*, and *Pitch*. This still seems to be the case Meyers (2009). Similarly, Orrell (2010) describes the difficulty for authors in finding and landing a literary agent to help them find a publisher.

4.2 The Model

4.2.1 Overview

There are two groups of risk neutral agents in the angel capital market: angels and entrepreneurs. Entrepreneurs have no capital, but each has an idea for a project that requires an upfront investment of *K*. Entrepreneurs differ in their productivity level; a mass E_H of the in total *E* entrepreneurs are high-productivity, while the remaining ones are low-productivity. Angels have no idea for a project, but do have the capital to fund one. They can either store their capital to earn a zero net return, or become active on the angel capital market with the intention to match with an entrepreneur and finance her project. For simplicity, normalize the mass of angels to $A = 1$. Assume $E \in \left[1, \overline{E}\right]$ where the upper bound $\overline{E} \geq 1$ is specified later.

Angels and the entrepreneurs can only meet after searching for each other. By assumption, search is free for angels, while entrepreneurs incur a search cost $\eta > 0$ in the process. This search cost includes shoe leather cost, the costs of composing a business plan, opportunity cost, etc. By assumption, the entrepreneurs' productivity levels are unknown to angels during the search and matching process.

A Pissarides-like matching function matches searching angels with searching entrepreneurs. But a key difference is that we allow angels to choose how hard to hide (the degree of elusiveness) which directly affects its functional form. By assumption, all angels hide equally hard, i.e. the chosen level of elusiveness is the "industry standard" in the angel capital market. Consequently, the number of matches depends on three components: the mass of searching entrepreneurs, the mass of searching angels, and the level of elusiveness chosen by the angels.

The timing of actions and events is as follows:

- Stage 1: Angels choose whether to be active on the angel capital market, and, if so, how hard to hide.
- Stage 2: Entrepreneurs decide whether to search.

- Stage 3: The matching technology matches active angels with searching entrepreneurs. A successfully matched angel-entrepreneur pair will be called a firm.
- Stage 4: The return is realized and shared between the parties according to an exogenous sharing rule known to both parties.

4.2.2 Firms

A firm is the outcome of an agreement to match between an entrepreneur and an angel. The firm produces a return that depends on the productivity level of the entrepreneur, R_L if the firm is managed by a low-productivity entrepreneur and $R_H > R_L$ with a high-productivity entrepreneur. By assumption, the productivity level of an entrepreneur is private information during the search stage and only revealed to the angel after investment takes place. Also, for simplicity, we assume that angels and entrepreneurs receive an exogenously determined fixed proportion of a firm's return. To make the problem relevant, we will assume that the angels' share $0 < \sigma < 1$ is large enough to make a possible match with a high-productivity entrepreneur worthwhile: $\sigma R_H - K > 0$. [36]

4.2.3 The Matching Technology

The matching technology has been studied at length in the labour literature. The angel capital market resembles the labour market in at least two ways. First, angels and entrepreneurs appear to engage in a search process in the same way as employers and unemployed workers in the labour market. Second, there may be traditional search frictions that characterize the angel capital market much like in the labour market, because of heterogeneity on both sides of the market combined with substantial information problems. A difference between the labour and the angel capital market is that angels often do not decide to reveal they are available to fund projects, whereas firms

[36] Our results do not depend on so-called variable bargaining power. See Engineer and Shi (1998, 2001) for a discussion of how variable bargaining power can generate new results in search models.

often do post job vacancies. Consequently, we employ a variation of the Pissarides' matching technology used in the labour market: [37]

$$m(a,e,h) = \left(\frac{1}{h}a\right)^{\alpha} e^{\beta} \qquad (1)$$

where α and β are parameters bounded by $(0,1)$, and m is the number of matches if the angels' hiding intensity is h, and there are $a \leq A$ active angels and $e \leq E$ searching entrepreneurs (that is, provided we have $m \leq \min\{a, e\}$ as the number of matches cannot exceed the mass of agents on either side of the angel market).

Apart from the parameter h the matching function is completely analogous to the standard matching technology in the labour literature. All else constant, an increase in e or a increases the number of matches at a diminishing rate. The probability of a match for an active angel and for a searching entrepreneur denoted by p_a and p_e respectively are

$$p_a(a,e,h) = \frac{\left(\frac{1}{h}a\right)^{\alpha} e^{\beta}}{a} = \left(\frac{1}{h}\right)^{\alpha} a^{\alpha-1} e^{\beta}$$ **Error! Bookmark not defined.**(2)

$$p_e(a,e,h) = \frac{\left(\frac{1}{h}a\right)^{\alpha} e^{\beta}}{e} = \left(\frac{1}{h}\right)^{\alpha} a^{\alpha} e^{\beta-1}$$ **Error! Bookmark not defined.**(3)

The key feature in our analysis is the inclusion of the hiding parameter *h*, which directly affects the severity of the search friction. Observe from equations (2) and (3) that the harder angels hide (larger *h*), the smaller the probabilities become for angels and entrepreneurs to match. In the extreme angels can essentially choose to sabotage the matching process; i.e, $\lim_{h\to\infty} p_a(a,e,h) = 0$ and $\lim_{h\to\infty} p_e(a,e,h) = 0$.

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[37] More generally we could have formulated the matching function $m(a,e,h) = \left(f(h)a\right)^{\alpha} e^{\beta}$ where $f'(h) < 0$ and $f''(h) > 0$. Our explicit form *f*(*h*) = 1/*h* satisfies this requirement.

Angels can also choose not to hide. Not hiding in some sense corresponds to Van Osnabrugge and Robinson's (2000) claim that an angel would be swamped with hundreds of project proposals if their information becomes widely known. In our model, we assume not hiding implies a matching probability of one for angels. Assuming there are enough searching angels, i.e. $a < e$, we have $m = a$ and hence $p_a\left(a,e,h\right)=1$ if $h=\left(a^{\alpha-1}e^{\beta}\right)^{1/\alpha}$. Without loss of generality we restrict the analysis to $h \geq h_{\min} \equiv E^{\beta/\alpha}$ -- this corresponds to a matching probability of one for angels if all *A*=1 angels and *E* entrepreneurs decided to enter the angel market: $p_a\left(1,E,h_{\min}\right)=1$.

4.3 Optimization and Equilibrium

Below we examine the agents' problems. In stage 2, entrepreneurs choose whether to search or not to search. Before that, in stage 1, angels choose hiding intensity to maximize their expected return from search. It can be shown that angels all choose to enter because a match with a high-productivity entrepreneur delivers positive profits and angels do not face search cost: *a = A = 1*.

4.3.1 The Entrepreneur's Problem

The expected return from search for a high-productivity entrepreneur is given by:

$$\pi_H(e,h) = p_e(1,e,h)(1-\sigma)R_H - \eta$$ **Error! Bookmark not defined.**(4)

It is the difference between the expected return of the project and the search cost η. A high-productivity entrepreneur chooses to search if and only if $\pi_{e_H}\left(a,e,h\right) \geq 0$. Similarly, the expected return from search for a low-productivity entrepreneur is

$$\pi_L(e,h) = p_e(1,e,h)(1-\sigma)R_L - \eta$$ **Error! Bookmark not defined.**(5)

and a low-productivity entrepreneur chooses to search if and only if $\pi_L\left(e,h\right)\geq 0$.
Observe that the expected returns between the types differ only because of the different project returns. As $R_H > R_L$, it follows that $\pi_H > \pi_L$. Thus, if the low-productivity entrepreneurs choose to search, $\pi_L \geq 0$, then so do the high-productivity entrepreneurs, $\pi_H > 0$. The converse is of course not necessarily true: if high-productivity entrepreneurs choose to search, $\pi_H \geq 0$, then low-productivity entrepreneurs may still find it unprofitable to search $\pi_L < 0$. This later situation occurs if the probability p_e lies within the following bounds

$$\frac{\eta}{(1-\sigma)R_H} \leq p_e < \frac{\eta}{(1-\sigma)R_L}$$

Moreover, if p_e is smaller than the left-hand bound, then no entrepreneurs search; if it is greater than the right-hand side bound, then all entrepreneurs search.
Substituting equation (3) into this condition allows us to express the bounds in terms of the hiding intensity, *h*.

$$ae^{\frac{\beta-1}{\alpha}}\frac{(1-\sigma)R_H}{\eta} \leq h < ae^{\frac{\beta-1}{\alpha}}\frac{(1-\sigma)R_L}{\eta} \quad (6)$$

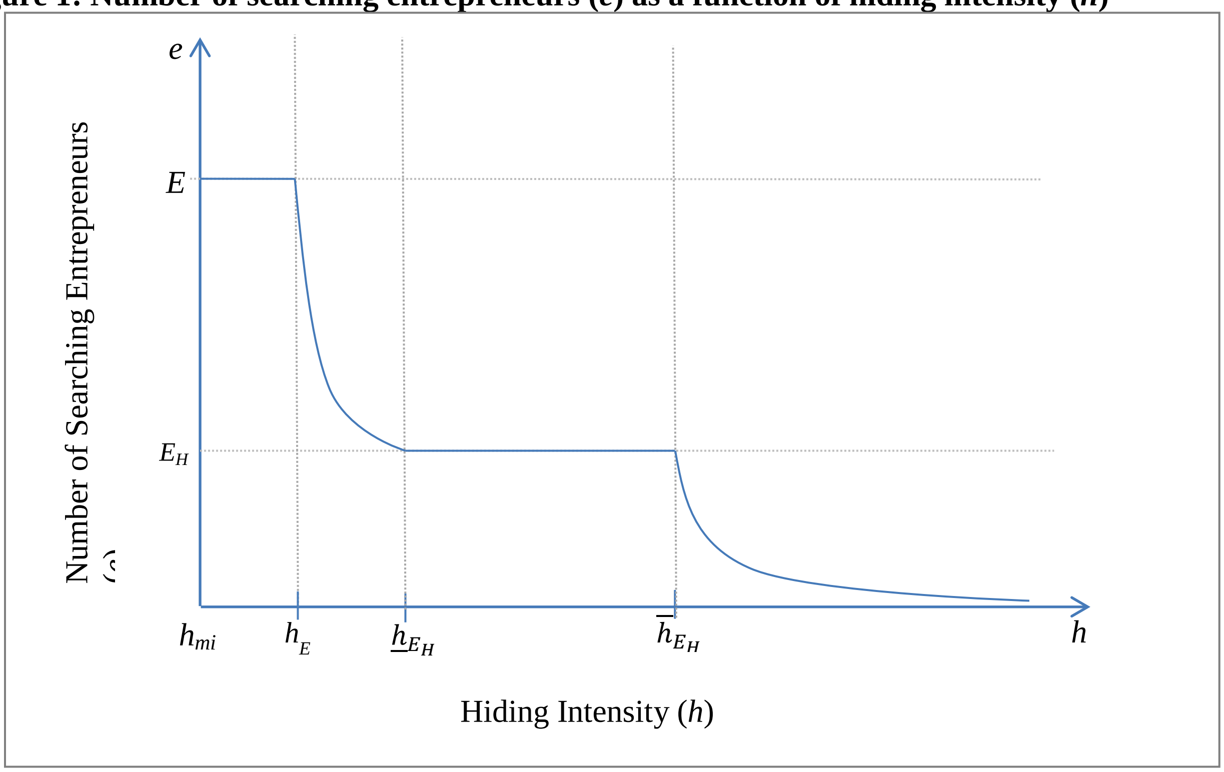
Error! Bookmark not defined.

Define h_{min} as a level of intensity such that all angels are active; h_E is the highest hiding intensity for which all entrepreneurs choose to search; $\underline{h}_{E_H}$ is the smallest *h* for which no low-productivity entrepreneurs choose to search; and $\overline{h}_{E_H}$ the greatest *h* for which all high-productivity entrepreneurs choose to search. Together this constitutes an expression for the number of searching entrepreneurs as function of e, which is presented in Figure 1 and in the following equation.

$$e(h)=\begin{cases} E & \text{for } h_{\min}\le h\le h_E \\ \left[\dfrac{1}{h}\right]^{\frac{\alpha}{1-\beta}}\bar{E}^{\frac{1}{1-\beta}} & \text{for } h_E<h<\underline{h}_{E_H} \\ E_H & \text{for } \underline{h}_{E_H}\le h\le \bar{h}_{E_H} \\ \left[\dfrac{1}{h}\right]^{\frac{\alpha}{1-\beta}}\left[\bar{E}\dfrac{R_H}{R_L}\right]^{\frac{1}{1-\beta}} & \text{for } h>\bar{h}_{E_H} \end{cases}$$

In equation (6) and Figure 1 we have assumed for convenience that $h_{\min}\le h_E$. At h_E an angel's matching probability is $p_a\left(1,E,h_E\right)=\dfrac{\eta E}{(1-\sigma)R_L}$. In Section 2.1 we introduced the upper bound on the mass of entrepreneurs, and assumed is exceeded one $\bar{E}\ge 1$. Defining hereby the upper bound to be $\bar{E}\equiv\dfrac{\left(1-\sigma\right)R_L}{\eta}$ we see that $h_{\min}\le h_E$.

Figure 1: Number of searching entrepreneurs (*e*) as a function of hiding intensity (*h*)



4.3.2 The representative angel's problem

In stage 1, angels anticipate entrepreneurs' entry behavior as described in equation (6). Therefore, a representative angel's expected profit function is given by

$$\pi_a(h) = p_a(1, e(h), h)\Pi_a(h)$$ **Error! Bookmark not defined.**(7)

Here $\Pi_a(h)$ represents the expected profit of a match for an angel. Letting $e_H(h) = \min\{e(h), E_H\}$ be the number of searching high-productivity entrepreneurs, we have

$$\Pi_a(h) = \sigma\left[\frac{e_H(h)}{e(h)} R_H + \frac{e(h) - e_H(h)}{e(h)} R_L\right] - K$$

Note that $\Pi_a(h)$ is bounded by $\Pi_a(h) \in \left[\underline{\Pi}_a, \overline{\Pi}_a\right]$, where

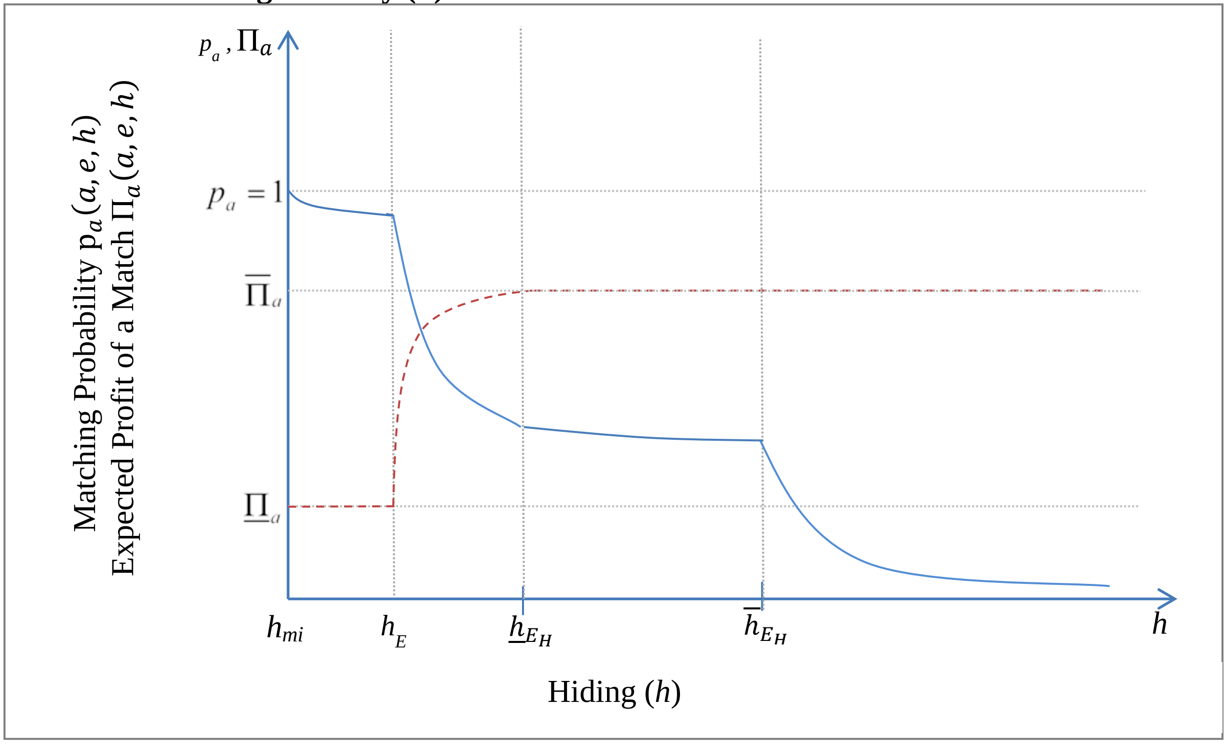
$$\underline{\Pi}_a \equiv \sigma\left[\frac{E_H}{E} R_H + \frac{E - E_H}{E} R_L\right] - K \geq 0 \text{ and } \overline{\Pi}_a = \sigma R_H - K$$

At the lower bound $\underline{\Pi}_a$ all entrepreneurs search, $e = E$, and at the upper bound $\overline{\Pi}_a$ only high-productivity entrepreneurs search, $e = e_H$. Figure 2 graphs the expected profit of a match $\Pi_a(h)$. The lower bound $\underline{\Pi}_a$ obtains for $h_{\min} \leq h \leq h_E$, and the upper bound $\overline{\Pi}_a$ obtains for $h \geq \underline{h}_{E_H}$.

The other component of expected profits is the matching probability $p_a(1, e(h), h)$. Figure 2 illustrates that $p_a(1, e(h), h)$ is decreasing in h. Taking the derivative of (2) with respect to h yields:

$$\frac{\partial p_a(1, e(h), h)}{\partial h} = -\alpha\left[\frac{1}{h}\right]^{\alpha+1} e(h)^{\beta} + \beta\left[\frac{1}{h}\right]^{\alpha} e'(h)^{\beta-1} < 0$$ **Error! Bookmark not defined.**(8)

Figure 2: Angel's matching probability (p_a) and expected profit of a match (Π_a) as a function of hiding intensity (h)



The first term on the right hand side describes the direct effect of an increase in h. An increase in h makes it more difficult for existing entrepreneurs to find angels and hence reduces the probability of an angel meeting an existing entrepreneur. This effect is negative throughout the range of h. The second term describes the indirect effect through $e(h)$ as described by (6). It is non-negative as $e'(h) \leq 0$ is shown in Figure 1. An increase in h makes it more costly for the entrepreneurs to search. Over parts of the range, $h_E < h < \underline{h}_{E_H}$ and $h > \overline{h}_{E_H}$, some existing entrepreneurs will cease searching. The kinks in Figure 2 correspond to this indirect effect turning on and off. In particular, the indirect effect turns off at $h = \underline{h}_{E_H}$, thus the slope of p_a is less steep at this point.

4.3.3. When Hiding Maximizes the profits of angels

Figure 2 reveals that there are three candidates for the profit maximizing h. First $h = \underline{h}_{E_H}$ generates greater profits than any $h > \underline{h}_{E_H}$. Second, there is the possibility of a profit maximizing h internal to the range $h_E \le h \le \underline{h}_{E_H}$; this is because payoff Π_a is increasing in h but p_a is decreasing in h. Third, $h = h_{\min}$ generates greater profits than $h_{\min} < h \le h_E$. The first two possibilities involve angels hiding sufficiently to discourage some entrepreneurs from searching. The third possibility is when angels do not hide. Figure 3 draws the profit function for the case where angels are best off hiding at $\underline{h}_{E_H}$.

In the Appendix we show that over the intermediate interval $h_E \le h \le \underline{h}_{E_H}$ the maximum profit is at $\underline{h}_{E_H}$ when $\underline{\Pi}_a \le \lambda \overline{\Pi}_a$ (or equivalently, the low-productivity project is unprofitable $\sigma R_L - K \le 0$); otherwise, the maximum is at h_E. As $h_{\min} \le h_E$, we can identify the maximum by comparing the profits from hiding at $\underline{h}_{E_H} = \left[\frac{\overline{E}}{(\lambda E)^{1-\beta}} \right]^{\frac{1}{\alpha}}$ to that from not hiding at $h_{\min} = E^{\beta/\alpha}$, where $E \le \overline{E} \equiv \frac{(1-\sigma)R_L}{\eta} \ge 1$. Angels are best off hiding at $\underline{h}_{E_H}$ if and only if $E \in [\underline{E}, \overline{E}]$, where

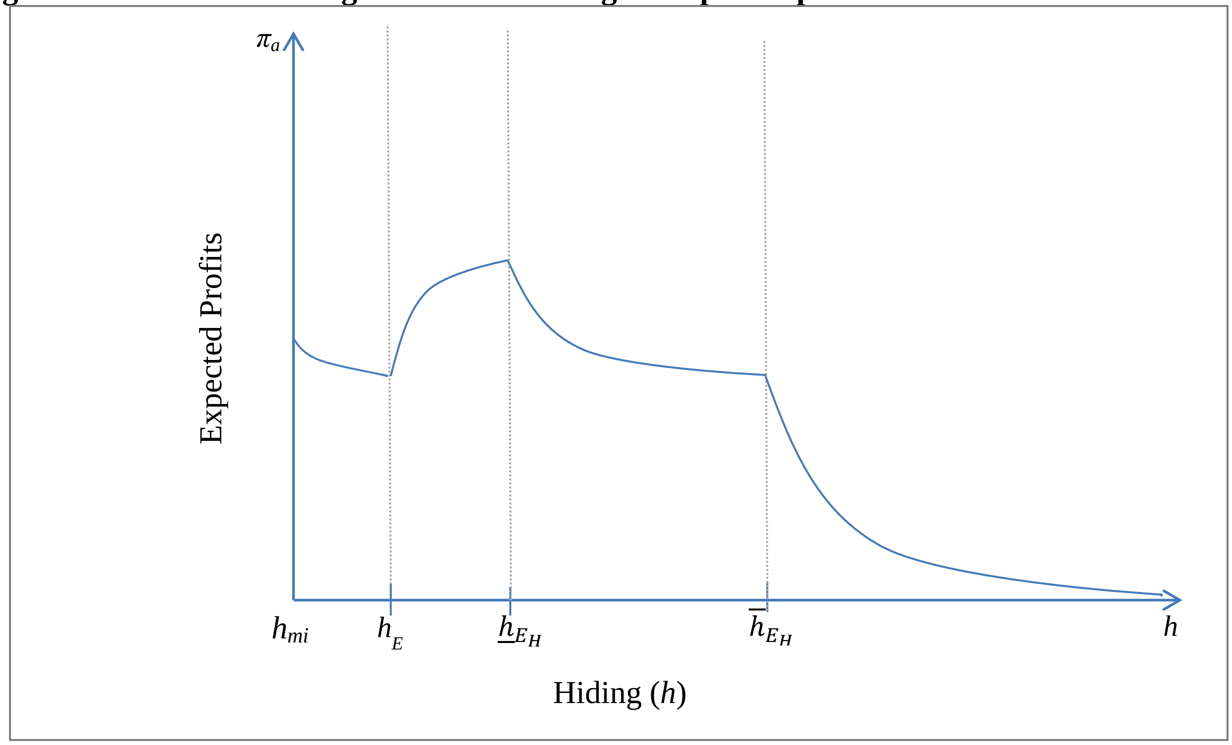
$$\underline{E} \equiv \max\left\{ \frac{\underline{\Pi}_a}{\lambda \overline{\Pi}_a} \overline{E}, 1 \right\}$$ **Error!**

Bookmark not defined.(9)

Hiding occurs over the whole range of E when $\underline{E} = 1$. Proposition 1 summarizes.

Proposition 1. If $\underline{\Pi}_a \le \lambda \overline{\Pi}_a$, then a non-empty interval $E \in [\underline{E}, \overline{E}]$ exists over which angels are best off hiding at $\underline{h}_{E_H}$; if the lower bound profit is sufficiently small, $\underline{\Pi}_a \le \lambda \overline{\Pi}_a / \overline{E}$, angels are best off hiding over the entire range $E \in [1, \overline{E}]$. Otherwise, *angels are best off not hiding at* h_{min}.

Figure 3: Case when hiding maximizes the angels' expected profits



The proofs to all the propositions are found in the Appendix.[38] Hiding at $\underline{h}_{E_H}$ discourages low-productivity entrepreneurs from searching while not discouraging high-productivity entrepreneurs from searching. This is an optimal strategy when the expected profits in a match of all entrepreneurs searching, $\underline{\Pi}_a$, is less than the expected profits in a match of just high-productivity entrepreneurs searching weighted by their proportion $\lambda\overline{\Pi}_a$. Observe that $\lambda \geq \underline{\Pi}_a / \overline{\Pi}_a$ is required for $\underline{E} \leq \overline{E}$. Hiding is only desirable when the proportion of high-productivity entrepreneurs is sufficiently great that it is worthwhile increasing h which has the negative consequence of reducing the chance of meeting a high quality entrepreneur.

[38] There exists combinations of parameters for which condition $\underline{\Pi}_a \leq \lambda\overline{\Pi}_a / \overline{E}$ is satisfied as we have assumed $0 \leq \underline{\Pi}_a < \overline{\Pi}_a$, $R_L > 0$, $0 < \lambda < 1$, $0 < \sigma < 1$ and $\eta > 0$. It can be shown that Proposition 1 extends to the case where the lower bound is non-positive, $\underline{\Pi}_a \leq 0$. Here condition $\underline{\Pi}_a \leq \lambda\overline{\Pi}_a / \overline{E}$ applies so that angels always hide at $\underline{h}_{E_H}$ and only high-productivity entrepreneurs search. Thus, angel profit is positive and all angels are active. Conversely, observe that if $\underline{\Pi}_a < 0$ we cannot have an equilibrium where angels do not hide because then all entrepreneurs search and angels would incur negative profits.

4.4 Social welfare

When does the representative angel's hiding choice maximize social surplus? To answer this question, we look at the constrained welfare optimum where the planner is constrained by the profit participation constraints of agents as well as the sharing rule σ. Thus, the planner only chooses *h.*

4.4.1 Maximizing Social Surplus

Expected social surplus is simply the population weighted sum of the expected profits of angels and entrepreneurs. As before all angels receive positive profits if active and therefore participate, a =1. The participation decision for entrepreneurs is again given by *e(h)* as described in equation (6). Substituting $e(h)$, the planner's problem is to choose h to maximize the following welfare function:

$$W(h) = m(1, e(h), h)\Pi_W(h) - \eta e(h)$$ **Error! Bookmark not defined.**(10)

where m is the number of matches given by equation (1) , and the expected social surplus in a match is given by $\Pi_W(h) = \frac{e_H(h)}{e(h)} R_H + \frac{e(h) - e_H(h)}{e(h)} R_L - K$. $\Pi_W(h)$ is bounded $\Pi_W(h) \in \left[\underline{\Pi}_W, \overline{\Pi}_W\right]$, where $\underline{\Pi}_W \equiv \frac{E_H}{E} R_H + \frac{E - E_H}{E} R_L - K$ and $\overline{\Pi}_W = R_H - K$.

The planner's problem has many of the same features as that of the representative angel's problem because we have

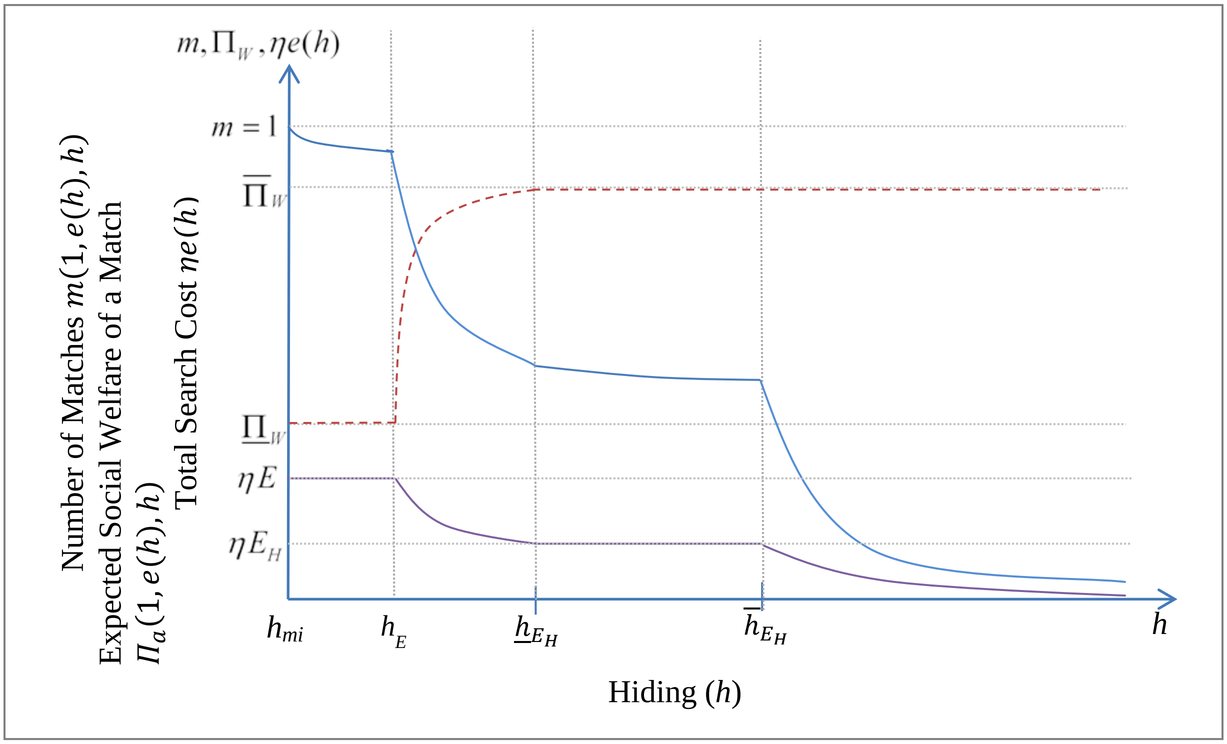
$$\sigma \Pi_W(h) = \Pi_a(h).$$

The only difference between the planner's problem and the angel's problem is that the former includes the entrepreneurs' costs of search, $\eta e(h)$. These costs are drawn in Figure 4 along with the profiles for number of matches and social surplus.

Figure 4 shows that, similar to the angel's problem, there is no internal optimum in the interval $h_E \le h \le \underline{h}_{E_H}$ and that again two candidates emerge as possible choices for *h.*

First $h = \underline{h}_{E_H}$ yields the greatest social surplus over the range $h \geq \underline{h}_{E_H}$. Second, $h = h_{\min}$ yields the greatest social surplus over the range $h \in [h_{\min}, h_E]$. The former implies hiding is socially optimal and the latter implies hiding is not socially optimal.

Figure 4: number of matches (*m*), expected social surplus of a match (Π_W), total search cost ($\eta e(h)$) as a function of hiding intensity (*h*)



It is socially optimal to hide when $W(\underline{h}_{E_H}) \geq W(h_{\min})$. In the Appendix we show this requires that the number of entrepreneurs is sufficiently large:

$$E \geq \underline{\underline{E}} \equiv \max\left\{ \left[\frac{\underline{\Pi}_W}{\frac{E_H}{E} \Psi \overline{\Pi}_W} \right] \overline{E}, 1 \right\}$$ **Error! Bookmark not defined.**(11)

where $\Psi = \dfrac{(E - E_H)(1-\sigma) R_L + E_H \overline{\Pi}_W}{E_H \overline{\Pi}_W} > 1$. It can be shown that $\underline{\underline{E}} = 1$ if and only if the lower bound surplus is sufficiently small, $\underline{\Pi}_W \leq \dfrac{E_H}{E} \Psi \overline{\Pi}_W / \overline{E}$. As $0 < \underline{\Pi}_W < \overline{\Pi}_W$, $R_L > 0$,

$0 < \lambda < 1$, $0 < \sigma < 1$ and $\eta > 0$ there exists combinations of parameters for which $\underline{\Pi}_W \leq \frac{E_H}{E}\Psi\overline{\Pi}_W / \overline{E}$ is satisfied. As before we consider the range of $E \leq \overline{E}$.

Proposition 2. If $\underline{\Pi}_a \leq \lambda\overline{\Pi}_a$, a non-empty interval $E \in \left[\underline{\underline{E}}, \overline{E}\right]$ exists over which hiding at $h = \underline{h}_{E_H}$ *maximizes social surplus, and if* $\underline{\Pi}_W \leq \frac{E_H}{E}\Psi\overline{\Pi}_W / \overline{E}$ it is socially optimal to hide over the entire range $E \in \left[1, \overline{E}\right]$. *Otherwise, not hiding at* $h = h_{\min}$ *is socially optimal.*

It turns out that to maximize social surplus, angels should only hide when the lower bound profit for angels is sufficiently small. This is a similar feature to the angel's profit maximizing problem. However, as we show below, there is a range of *E* where angels should not hide according to the surplus maximizing criteria.

4.4.2 When Angels Should and Should not Hide

Comparing Propositions 1 and 2 reveal that there is only one case in which hiding prescriptions differ: $\underline{\Pi}_a < \frac{E_H}{E}\overline{\Pi}_a$ and $\underline{E} \neq \underline{\underline{E}}$. In the Appendix we show that $\underline{E} < \underline{\underline{E}}$ provided that social surplus maximization does not always involve hiding $\underline{\underline{E}} > 1$ (or, equivalently, $\underline{\Pi}_W > \frac{E_H}{E}\Psi\overline{\Pi}_W / \overline{E}$). We have the following proposition.

Proposition 3. Angels profit maximizing hiding behavior maximizes social surplus in all cases except one: if $\underline{\Pi}_a < \frac{E_H}{E}\overline{\Pi}_a$ and $\underline{\underline{E}} > 1$, *a non-empty interval* $E \in \left[\underline{E}, \underline{\underline{E}}\right)$ exists over which angels hide at $h = \underline{h}_{E_H}$ but social surplus maximization involves not hiding at $h = h_{\min}$.

Angels may hide over a greater range of E than is socially desirable. This is the case because angels do not consider the aggregate search cost incurred by the searching entrepreneurs. This is shown in Figure 4. If the cost of search η to the entrepreneurs is equal to 0, then the aggregate search cost function ηE is flat at zero. In this case Figure 4 would resemble Figure 2 which sketches the angel's optimization problem. Equation (10) also clarifies the relationship between the angel's problem and the planner's problem. If the cost of search η to the entrepreneurs is equal to 0, the only difference between the angel's problem and the planner's problem is a , namely sigma, σ.

In the Appendix, we show the source of the divergence between private angel incentives and social welfare is related to the term $\left(1-\sigma\right)\left[\frac{E_H}{E}R_H+\frac{E-E_H}{E}R_L\right]>0$ which describes the average project return across all entrepreneurs. The planner hides over a smaller interval because this average return includes the surplus for low quality entrepreneurs. Other factors affect the length of the interval $E\in\left[\underline{E},\underline{\underline{E}}\right)$. For example, increasing entrepreneur's search cost, η, decreases the interval.

4.5 Conclusion

Search in some markets does not fit into either the traditional matching search theory (e.g. Mortensen and Pissarides (1994)) or directed search (e.g. Julien et. al. (2000), Burdett et. al. (2001)). These theories assume inherent frictions related to physical, information or coordination impediments. However, in some markets, the main impediment for matches is an endogenous search friction created by the hiding behavior on one side of the market. Hiding behavior induces search effort by the other side of the market and imposed search costs can hence form a screening mechanism. We have made the argument that the angel capital market is one market that is described by such hide and seek search. Angels hide to avoid being inundated by the low-productivity entrepreneurs. At the same time, angels hope to be sought out and found by the high-productivity entrepreneurs. They can do this by choosing to be elusive but not too elusive. In this way, only high-productivity entrepreneurs enter the search, as they are the only ones that generate sufficient surplus to compensate for the higher search cost.

In this paper, we model hide and seek behavior in the context of our leading example of the angel capital market. By choosing how hard to hide, angels change a parameter of the standard labor-search matching technology. In our model, angels can ensure complete matching by not hiding, while hiding results in incomplete matching. Angels only hide to discourage low-quality entrepreneurs when an encounter would result into a negative profit. We also examine when angels profit-maximizing hiding choice maximizes social surplus. If angels are best off not to hide, then not hiding also maximizes social surplus. However, depending on parameters, the choice to hide may be to the detriment of social surplus.

Our hide and seek model is kept simple. For example, we have not included hiding costs. If hiding costs were positive then the parameter space over which hiding would be optimal for angels and the planner would be smaller. With prohibitive hiding costs, angels would never hide. We have set our model so that no hiding corresponds to complete matching. We did this deliberately to underscore our main point that search maybe induced, rather than a result of technology. However, in a more general Pissarides type model, zero hiding might well correspond to incomplete matching, and we could model negative hiding similar to advertising as in Pissarides (2000, Chapter 5). More generally, there could be costs to both hiding and advertising and depending on parameters agents might take different hiding and advertising strategies. We leave these and other extensions of our hide and seek search framework to future research.

4.6 Appendix

4.6.1 Proof of Proposition 1

Recall that $p_a > 0$ and we assumed that $\underline{\Pi}_a > 0$. Thus, $\pi_a = p_a(1, e(h), h)\Pi_a\left(h\right) > 0$ and all angels choose to be active a=A=1. Substituting for p_a from (2) and *e(h)* from (6) into π_a gives the unconstrained representative angel's profit maximization problem.

$$\max_h \pi_a = \begin{cases} \dfrac{1}{h^\alpha} E^\beta \underline{\Pi}_a & \text{for } h_{\min} \le h \le h_E \\ \dfrac{E_H}{\overline{E}}\sigma\left[R_H - R_L\right] + \left(\dfrac{1}{h}\right)^{\frac{\alpha}{1-\beta}} \left(\overline{E}\right)^{\frac{\beta}{1-\beta}} \left[\dfrac{\underline{\Pi}_a - \dfrac{E_H}{\overline{E}}\overline{\Pi}}{\dfrac{\overline{E} - E_H}{\overline{E}}}\right] & \text{for } h_E < h < \underline{h}_{E_H} \\ \dfrac{1}{h^\alpha} E_H{}^\beta \overline{\Pi}_a & \text{for } \underline{h}_{E_H} \le h \le \overline{h}_{E_H} \\ \left(\dfrac{1}{h}\right)^{\frac{\alpha}{1-\beta}} \left[\overline{E}\dfrac{R_H}{R_L}\right]^{\frac{1}{1-\beta}} \overline{\Pi}_a & \text{for } h > \overline{h}_{E_H} \end{cases}$$

For $h_{\min} \le h \le h_E$ profit is declining in h so that h_{min} gives the greatest profit. As h_{min} corresponds to p_a = 1, $h_{\min} \equiv E^{\beta/\alpha}$ and the corresponding profit is $\pi_a(h_{\min}) = \underline{\Pi}_a$. **Error! Bookmark not defined.**

Similarly, for $h \ge \underline{h}_{E_H}$ profit is declining in h so that $\underline{h}_{E_H}$ gives the greatest profit. As $\underline{h}_{E_H}$ corresponds the smallest value of h that gives $e = E_H$ .We find $\underline{h}_{E_H} \equiv \left[\dfrac{\overline{E}}{E_H{}^{1-\beta}}\right]^{\frac{1}{\alpha}}$ and

$$\pi_a\left(\underline{h}_{E_H}\right) = \frac{E_H}{\overline{E}}\overline{\Pi}_a$$ **Error! Bookmark not defined.**

Over the intermediate interval $h_E \le h \le \underline{h}_{E_H}$ the change in expected profits depends the lower bound profits (or equivalently, on the sign of $\sigma R_L - K$): if $\underline{\Pi}_a \le \dfrac{E_H}{E}\overline{\Pi}_a$, then expected profits are weakly increasing in h and the maximum is at $\underline{h}_{E_H}$; if $\underline{\Pi}_a > \frac{E_H}{E}\overline{\Pi}_a$, then expected profits are decreasing and the maximum is at h_E. As profits at h_{min} exceeds profits at h_E the problem reduces to comparing profits at h_{min} to $\underline{h}_{E_H}$.

Angels are best off hiding if and only if $\pi_a\left(\underline{h}_{E_H}\right) \geq \pi_a\left(h_{\min}\right)$. Substituting for profits from above gives the lower bound $\underline{E}$ in (9). As we have restricted $E \leq \overline{E}$, angels are best off hiding if and only if $E \in \left[\underline{E}, \overline{E}\right]$. As described in the text, this interval is non-empty if and only if $\underline{\Pi}_a \leq \frac{E_H}{E}\overline{\Pi}_a$. Otherwise, angels are best off not hiding at h_{min}. ■

4.6.2 Proof of Proposition 2

The social welfare function is given by (10). The planner's problem is as follows:

$$\max_h W(h) = \begin{cases} \frac{1}{h^\alpha} E^\beta \underline{\Pi}_W - \eta E & \text{for } h_{\min} \leq h \leq h_E \\ \frac{E_H}{\overline{E}}\left(R_H - R_L\right) + \left(\frac{1}{h}\right)^{\frac{\alpha}{1-\beta}} \left(\overline{E}\right)^{\frac{\beta}{1-\beta}} \left[\frac{\underline{\Pi}_a - \frac{E_H}{E}\overline{\Pi}_a}{\frac{E_H}{E}}\right] & \text{for } h_E < h < \underline{h}_{E_H} \\ \frac{1}{h^\alpha} {E_H}^\beta \overline{\Pi}_W - \eta E_H & \text{for } \underline{h}_{E_H} \leq h \leq \overline{h}_{E_H} \\ \left[\frac{1}{h}\right]^{\frac{\alpha}{1-\beta}} \left[\overline{E}\frac{R_H}{R_L}\right]^{\frac{\beta}{1-\beta}} \left\{\overline{\Pi}_W - \eta\left[\overline{E}\frac{R_H}{R_L}\right]\right\} & \text{for } h > \overline{h}_{E_H} \end{cases}$$

For $h_{\min} \leq h \leq h_E$ social welfare is declining in h so that $h_{\min} \equiv E^{\beta/\alpha}$ gives the greatest social welfare. The corresponding social welfare is given by $W(h_{\min}) = \underline{\Pi}_W - \eta E$.

Similarly, for $h \geq \underline{h}_{E_H}$ profit is declining in h so that $\underline{h}_{E_H} \equiv \left[\frac{\overline{E}}{{E_H}^{1-\beta}}\right]^{\frac{1}{\alpha}}$ gives the greatest social surplus. The corresponding social welfare is given by $W\left(\underline{h}_{E_H}\right) = \left(\frac{E_H}{\overline{E}}\overline{\Pi}_W - \eta E_H\right)$. **Error! Bookmark not defined.**

In the interval $h_E < h < \underline{h}_{E_H}$ the social surplus is increasing in *h* if $\underline{\Pi}_a < \frac{E_H}{E}\overline{\Pi}_a$, constant if $\underline{\Pi}_a = \frac{E_H}{E}\overline{\Pi}_a$ and decreasing if $\underline{\Pi}_a > \frac{E_H}{E}\overline{\Pi}_a$. Thus, as in Proof of Proposition 1, finding the social maximization *h* reduces to comparing social welfare at h_{min} to $\underline{h}_{E_H}$.

Hiding is social optimal if and only if $W\left(\underline{h}_{E_H}\right) \geq W\left(h_{\min}\right)$. Substituting in the above welfare values gives the lower bound $\underline{\underline{E}}$ in (11). As we restrict $E \leq \overline{E}$, social surplus maximization involves angels hiding when $E \in \left[\underline{\underline{E}}, \overline{E}\right]$.

Finally, we show that $\underline{\underline{E}} \leq \overline{E}$ if and only if $\underline{\Pi}_a \leq \frac{E_H}{E}\overline{\Pi}_a$. Substituting from (11) gives

$$\underline{\underline{E}} = \left[\frac{\underline{\Pi}_W}{\frac{E_H}{E}\Psi\overline{\Pi}_W}\right]\overline{E} \leq \overline{E}$$

The inequality implies $\frac{\underline{\Pi}_W}{\frac{E_H}{E}\overline{\Pi}_W} \leq \Psi$ and substituting for Ψ gives $\underline{\Pi}_a \leq \frac{E_H}{E}\overline{\Pi}_a$. ■

4.6.3 Proof of Proposition 3

The hiding behavior of angels is social suboptimal when

$$\underline{E} - \underline{\underline{E}} = \max\left\{\frac{\underline{\Pi}_a}{\frac{E_H}{E}\overline{\Pi}_a}\overline{E}, 1\right\} - \max\left\{\frac{1}{\Psi}\frac{\underline{\Pi}_W}{\frac{E_H}{E}\overline{\Pi}_W}\overline{E}, 1\right\} < 0$$

whenever $\underline{\Pi}_a < \frac{E_H}{E}\overline{\Pi}_a$ and $\underline{\underline{E}} > 1$. Ignoring the lower bound values of 1 gives the unconstrained difference

$$\frac{\overline{E}}{\frac{E_H}{E}}\left[\frac{\underline{\Pi}_a}{\overline{\Pi}_a}-\frac{\underline{\Pi}_W}{\Psi\overline{\Pi}_W}\right]<0$$

Substituting for $\underline{\Pi}_a, \overline{\Pi}_a, \underline{\Pi}_W, \overline{\Pi}_W, \Psi$ gives the following inequality

$$\frac{\left(E-E_H\right)\left(\sigma R_L-K\right)}{E_H\left(\sigma R_H-K\right)}<\frac{\left(E-E_H\right)\left(\sigma R_L-K\right)}{E_H\left(R_H-K\right)+\left(E-E_H\right)\left(1-\sigma\right)R_L}$$

$$0<E_H\sigma R_H-E_H R_H+\left(E-E_H\right)\left(1-\sigma\right)R_L$$

As $\underline{\Pi}_a<\frac{E_H}{E}\overline{\Pi}_a$ implies $\sigma R_L-K<0$, it can simplify to $\left(1-\sigma\right)\left[E_H R_H+\left(E-E_H\right)R_L\right]>0$, which is a true statement. This completes the proof. ■

Chapter 5: Conclusion

It is well documented that capital financing is the main factor determining the likelihood of starting and growing a new high-growth venture. To survive and to grow, start-up ventures typically rely on two main sources of external financing: angel investors and venture capitalists.

In the recent years, it has been documented that angel investing supplies more capital to early-stage companies than do venture capitalists. A recent OECD (2011) report estimates that the total angel market is approximately the same size as the venture capital market in the United States, Canada and some European countries. Importantly, Wiltbank (2005a, 2005b) finds that angel capital is the main driver for most of the economic growth and job creation in the United States.

In spite of its importance, research on angel capital investment is quite limited due to the paucity of the data on angel investment. This dissertation contributes to the literature by constructing and analyzing a detailed data set assembled from the British Columbia Venture Capital Program. This data set provides a unique opportunity to test theories about the angel capital market.

Chapter 2 empirically examines the relationship between angel investors and venture capitalists in financing early-stage entrepreneurial ventures. This chapter juxtaposes a complements hypothesis, where angel financing is a springboard for venture capital, against a substitutes hypothesis, where angels and venture capital are distinct financing methods that ought not to be combined. This chapter analyzes these hypotheses under two contexts: the dynamic investment pattern context and the company performance. Using a unique detailed dataset of start-ups in British Columbia, Canada, this chapter shows that companies that obtain angel financing subsequently obtain less venture capital, and vice versa. This substitutes pattern is more pronounced for companies funded by less experienced angels. In term of performance, this chapter reports that on average companies funded by venture capital do better than angel backed companies, as measured by revenues or successful exits, and venture capitalists make larger investments. Mixing angel and venture capital funding tends to be associated with worse performance. Overall the evidence favors the substitutes hypothesis.

Chapter 3 empirically studies the role of geographic distance on angel investment performance. This chapter hypothesizes four possible channels through which distance may play a role in determining angel investment performance. The information effect and objectivity effect occur at the selection stage. The advising effect and network effect occur at the value-added stage. Using the British Columbia Venture Capital Program data, this chapter shows that the return to angel investment is positively related to distance. Examining the relationship of distance across different categories of angel investors, across angel investor's locations, and across company's location, reveals that the returns to distance are largest for the smallest and least experienced angel investors and for companies located in a center. These findings suggest that the positive relationship between distance and return is dominantly driven by the objectivity effect, where local angel investors who might be unduly swayed by an enthusiastic entrepreneur.

Chapter 4 adopts of a search framework introduced by Pissarides (2000) that is commonly used in the labor literature to explain why it is generally hard for entrepreneurs to find angel investors. Angel's hiding behaviour forces entrepreneurs to engage in a costly search. In the model, high-productivity entrepreneurs have a greater value of search than low-productivity entrepreneurs. Therefore, angel investors endogenously choose the hiding strategy to screen out low-productivity entrepreneurs who would otherwise swamp the market. Interestingly, social surplus is often increased when angels hide, though in some circumstances surplus may fall. "Hide and seek search" stands in contrast to the traditional search theory, where the search friction represents inherent physical and informational impediments to trade, as well as directed search, where inherent coordination problems generate impediments to matches.

Of course, the results of this dissertation should be interpreted taking into account the shortcomings associated with the data and analysis as well as the simplifications in the theoretical model. Nevertheless, the clear patterns and arguments found in this dissertation should be of interest to not only policy makers but also potential investors and entrepreneurs who are and will seek capital in the venture capital market. Finally, these results serve as an inspiration to the academic to pay more attention to this important but under-studied area of private equity financing.

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