Angels and Venture Capitalists: Substitutes or Complements?

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Abstract

Understanding an entrepreneurial finance ecosystem requires an appreciation of how different investors interact with each other. Angels and venture capitalists constitute two very important investors in start-ups. We develop and empirically test hypotheses about the interactions between these two investor types. The focus is on the dynamics of the funding path of start-up companies. We ask whether angels and VCs are complements or substitutes, and also whether funding decisions are primarily investor- or company-led. Using a unique database from British Columbia, Canada, we show that angels and VCs are dynamic substitutes. An instrumental variable approach based on available tax credits for investors suggests that the substitutes relationship is company-led. The dynamic substitutes pattern applies across the performance range for companies. It is more pronounced for casual angels and angel funds than for serial angels. Overall, the evidence from the entrepreneurial finance ecosystem in British Columbia suggests the presence of parallel streams for angel and VC funding, with fewer transitions across streams than is traditionally assumed.

1. Introduction

Entrepreneurial finance occurs within an ecosystem of diverse investors, where start-up companies obtain funding from multiple investors over multiple rounds of financing. Individual private investors, commonly referred to as 'angel investors' (or just 'angels'), and professional venture capitalists (VCs henceforth), are at the center of the entrepreneurial finance ecosystem. An OECD report from 2011 notes that "While VC 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 VC" (OECD 2011, p.10).[1] While there is an established literature on VC finance, the literatures on angel financing or the broader entrepreneurial finance ecosystem remain relatively underdeveloped.

To comprehend the workings of an entrepreneurial finance ecosystem we need to understand how the different investor types interact with each other. In this paper we develop and empirically test alternative hypotheses about the nature of interactions between investors in start-up companies, with a special focus on angel investors and VCs. Throughout the analysis we leverage the dynamic structure of how start-ups are funded across multiple financing rounds. Our hypotheses recognize the possibility that different types of investors can be complements or substitutes to each other. In addition, we emphasize that the dynamic funding choices can be led by either the company or its investors.

To motivate our analysis of complements versus substitutes, we note that there are two opposing views on the relationship between angels and VCs. The first and probably dominant view sees angels and VCs as synergistic members of a tightly knit ecosystem. They may have different skills and networks, not to mention different amounts to invest, and companies benefit from the combination of the attributes of these investor types. For example, Marc Andreessen, venture capitalist and founder of Netscape, notes that "[…] to get the best introductions to the A stage venture firms is to work through the seed investors […]" (Sanghvi, 2014). Under this view, angel financing is a prelude to obtaining VC. Benjamin and Margulis (2000) note: "Angel investment runs the critical first leg of the relay race, passing the baton to VC only

[1] OECD (2011) estimates that the total angel market is approximately the same size as the VC market, an estimate in line with earlier studies (e.g. Mason and Harrison, 2002; Sohl, 2003).

after a company has begun to find its stride." The well-known examples of Google and Facebook powerfully illustrate this logic.

The second view sees angels and VCs as offering companies separate financing paths that rarely cross each other. They are alternative financing modes and companies that obtain funding from one type of investor are more likely to stick to that investor type. This could be because certain company attributes lend themselves better to one type of financing mode (i.e. a selection reason), and/or because once companies have receiving funding the investors explicitly or implicitly guide their companies towards a path involving investors of their own type (i.e. treatment).[2] The view that start-up companies may be better off sticking to angel financing and avoiding venture capital altogether has become more popular in recent years, and is explained in greater detail by Ibrahim (2013) and Peters (2009). Furthermore, Mason, Botelho, and Harrison (2016) argue that the rise of angel networks and angel funds plays an important role in the possible avoidance of VCs, as it makes larger rounds of follow-on financing by angel syndicates possible.

The biggest obstacle to understanding the role of angels in the market for entrepreneurial finance has been the lack of access to credible and systematic data. We collected data related to a government program in British Columbia, Canada (BC), where tax credits are available not only to VC firms but also to angel investors (Government of British Columbia, 2017; Hellmann and Schure, 2010). The registration and filings under BC's Investment Capital Program (BCICP) offer a unique opportunity to obtain systematic and detailed data on both angel and VC investments. The distinctive feature of our data is the information about all the individual shareholders of our companies over time. This allows us to construct detailed financing histories of start-up companies. We observe the financial history of 469 BC start-up companies that were funded over the period 1995-2009. In line with the focus of the BCICP, the bulk of the companies are technology-based.

The ecosystem interaction of interest in this paper concerns the dynamics of the investor composition of companies. Specifically, we ask how the prior presence of investor types relates to subsequent investor

[2] Examples of successful angel-backed start-ups that never raised venture capital include Smartcell, which got acquired by Merck, or Club Penguin which was acquired by Disney.

composition. Our regressions at the company-round level contain a rich set of controls, including company characteristics and a variety of time clocks. First, we find strong evidence for dynamic persistence within investor types. A company that already obtained funding from one particular type of investor is likely to raise more funding from investors of the same type. This effect is not driven by follow-on funding from existing investors as our analysis makes clear. We also show that the dynamic persistence result is not driven by for example the number of financing rounds of companies are involved in. Second, we find significant negative dynamic effects between angel and VC financing. Companies that obtained more angel financing in the past are less likely to subsequently obtain VC funding; and vice versa. These main findings are robust to alternative model specifications.

Our theoretical framework distinguishes between investor-led and company-led financing choices. In case of the former, investors affect the future funding choices of companies, while in the latter case company characteristics determine the evolution of investor choices. These hypotheses can be tested empirically by recognizing that investor-led choices translate into investor treatment effects, whereas company-led choices translate into (potentially unobservable) selection effects. To empirically separate selection and treatment effects we exploit variation in the tax credit program that affected the relative availability of angel and VC financing. We find that our instruments generate significant coefficients in the first stage regression, while all key coefficients turn insignificant in the second stage regression. This is consistent with the presence of a selection, rather than a treatment effect and suggests that company characteristics drive dynamic investor choices.

One potential concern with our 'parallel streams' result is that it may be generated by poorly performing angel-backed companies that rely on on-going angel financing, because they are not good enough to 'graduate' to the VC stage. Under this view only the very best companies (the 'Googles and Facebooks') graduate from angel financing to VC. We call this the quality-contingent complements hypothesis. To address this, we examine how the dynamic substitutes pattern varies with company performance. We follow the prior literature (see e.g. Phalippou and Gottschalg, 2009) and use exit outcomes as a proxy for company performance. Specifically, we separate our data into companies that eventually had an exit (IPO or a "successful acquisition" – to be defined more precisely below), stayed alive, or failed. We find that the substitutes pattern of companies with a successful exit is very similar to that of companies who failed, suggesting that performance is unlikely to drive our results, and rejecting the quality-contingent complements hypothesis.

Our data allows us to distinguish between different subtypes of investors. We classify angels into: 'casual angels' who only invest in a single company; 'serial angels' who invest in multiple companies (and are presumable more committed to angel investing), and thus are likely to be more committed to angel investing; and 'angel funds' that combine the funding of multiple angels into an investment vehicle. We find that the substitutes pattern between angels and VCs applies to casual angels and to angel funds, but not to serial angels. This result suggests, first of all, that heterogeneity within the angel community matters, and, secondly, that serial angels are less disconnected from the VC community than other types of angels.

Overall, our findings challenge some of the received wisdom about entrepreneurial finance ecosystems which are often portrayed as tightly interconnected systems in which successful angel-backed companies migrate to VC funding in later stages. Such migrations are indeed observed in our data, but our results show that they are not the norm. One important qualifier is that our results occur in the context of one specific entrepreneurial finance ecosystem, namely that of British Columbia. Much of the received wisdom about angel and venture capital financing comes from Silicon Valley in the 1990s, which may be very different from other ecosystems, including, the Silicon Valley of the present.

An important open question for future research is therefore to investigate to what extent our results carry over to other high-tech clusters. Another important qualifier is that our substitutes pattern applies to casual angels who only invest once, but not to serial angels who make many investments. Much of the received wisdom, including the prominent examples from Silicon Valley mentioned above, apply to prominently visible serial angels. Our analysis suggests that distinguishing among different types of angels matters and confirms suggestions that for, example, visible and invisible angels tend to be very different (OECD, 2011; Engineer, Schure, and Vo, 2019). We hope that our analysis spurns further research into the inner workings of start-up financing ecosystems.

Our findings suggest some preliminary policy implications. Policies that aim to foster entrepreneurial finance typically target the VC industry (Lerner 2008), and rarely angel investors (Sandler, 2004; Wilson, 2015). If the financial ecosystem consisted of a single stream, such a VC-centered policy would affect all the relevant companies either directly or indirectly. However, in ecosystems characterised by parallel streams a VC-centered policy will fail to reach "angel-type" companies. Instead, our findings suggest that programs that target angels do not merely prime the pump for venture capital, but have a distinct purpose of catering to a differentiated set of start-up companies.

The remainder of this paper is structured as follows. Section 2 develops the main hypotheses and discusses the relationship to the literature. Section 3 discusses our data. Section 4 estimates our empirical models of the dynamic financing patterns across different investor types. The distinction between investor-led versus company-led interactions is analyzed in Section 5. Section 6 examines the possibility that companies sort on quality and Section 7 the role of the differences between investor subtypes. Section 8 concludes. The Online Appendix to this paper contains additional detail on the BCICP and presents the tables of a number of alternative regressions that we mention in the text. It also explains how we categorized investors into types and subtypes and presents details of a simulation study we use to clarify the validity of our main regression model.

2. Hypotheses and literature

2.1 Theoretical framework

We provide a verbal theoretic framework about the interrelationship between angels and VCs that is based on two fundamental questions. The first question is whether investor types are complements or substitutes. Our notion of complements is that both angels and VCs belong to a common financing environment, where they play complementary roles. For example, a common view is that angels take care of seed funding, and that companies that survive the seed stage proceed to VC funding. By contrast, our notion of substitutes is that angels and VCs represent distinct financing paths. Companies switching between angels and VCs would be the exception rather than the rule.

The second question is whether the dynamic financing choices are led by investors or companies. Investor-led means that once a company has matched with investors, those investors play an important role in determining the company's future financing choices. Company-led means that companies have (observable or unobservable) characteristics that determine their dynamic financing choices. Econometrically speaking, investor-led corresponds to a treatment effect, whereas company-led corresponds to a selection effect.

The two fundamental questions yield four hypotheses about companies' dynamic financing pattern across angels and VCs: investor-led complements, investor-led substitutes, company-led complements, and company-led substitutes. In principle we can apply these four hypotheses to any two investor types and any potential migrations between them. For brevity's sake, we focus here on the possible transitions from angel to VC financing. Figure 1 shows a simple two-by-two matrix that summarizes the four main hypotheses, as applied to possible angel to VC transitions.

Figure 1: Hypotheses about the transition from angel to VC funding

	Investor-led	Company-led
Complements	Angels are a <u>launch pad</u> that actively help a company to get to VC funding	Angels are a <u>stepping stone</u> that a company gets through on the way to VC funding
Substitutes	Angels are a <u>sink hole</u>. They encourage companies to remain angel funded and avoid VC	Angels are a <u>parallel stream</u> for funding companies, i.e., an alternative to VC funding

<u>Launch pad</u>: Angels play an active role in preparing companies to raise VC funding, i.e., they actively help companies to obtain subsequent VC funding. The launch pad hypothesis has an empirically testable implication, namely that a random allocation of angel capital should increase a company's probability of subsequently raising venture capital. Specifically, when more angel capital is available (say because of an increase in available tax credits), then we would expect that more companies raise angel financing (as well as angel-backed companies raising more angel financing). For the additional companies that now obtain angel funding, the launch pad theory predicts that they will be steered towards venture capital.

Stepping stone: Angels are part of a company's path towards raising VC, but they do not play an active role in steering companies to VC funding. Rather, company characteristics determine the path. If companies are exposed to a random supply shock of angel capital, the probability of companies getting angel financing increases. However, the chance of subsequent VC funding remains unaffected under the stepping stone hypothesis, because angels do not actively steer companies toward VCs.

Sink hole: Once a company enters the angel world, it becomes less likely to raise VC funding in future rounds. Angels direct companies towards more angel funding, and away from VCs. Under this hypothesis, a random increase in angel capital makes it less likely that companies subsequently raise VC funding.

Parallel streams: Companies self-select into the financing path that works the best for them. Companies that suit the angel model are unlikely to switch from angels to VCs, because their needs are best met by the angel model. A random supply increase of angel capital does not affect a company's likelihood of obtaining VC. This is because it is company characteristics that determine investor choices.

Our simple theoretical framework generates four distinct hypotheses that are empirically testable. Specifically, the 'launch pad' and 'stepping stone' hypotheses predict a positive correlation between past angel investments and obtaining VC funding, whereas the 'sink hole' and 'parallel stream' hypotheses predict a negative correlation. To distinguish between investor-led versus company-led hypotheses one needs to look at random supply shocks – in our empirical analysis this will involve instrumental variable estimation. The 'launch pad' and 'sink hole' hypotheses are based on treatment effects and should therefore be affected by random supply shocks. By contrast, the 'stepping stone' and 'parallel stream' hypotheses are based on selection effects and should remain unaffected by random supply shocks.[3]

2.2 Related literature

[3] Again, our theory discussion focused on the transition from angel to VC funding, but the same framework can be applied to any other potential transitions across investor types (or investor subtypes, as discussed in Section 7). For example, if we looked at VC to angel transitions, then, under a sink hole hypothesis, VCs would keep their companies to themselves and actively discourage them from seeking any subsequent angel financing; under a parallel streams hypothesis, companies with VC funding would rarely be in need for obtaining later-stage angel financing.

As the recent literature review by Tenca, Croce, and Ughetto (2018) makes clear, the academic literature on angel financing has grown substantially, but remains underdeveloped. Research on angels is hampered by a shortage of reliable data (as the market is largely informal) and, often, the lack of a proper counterfactual. Furthermore, much of what we know about angel investors is based on merely a part of the angel community, namely those associated with angel networks (OECD 2011). Kerr, Lerner, and Schoar (2014) examine data from two angel funds that keep track of which companies presented in front of the group, and which companies actually received funding. 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 do not consider the context of the broader ecosystem, which the cross-county study of Lerner, Schoar, Sokolinski, Wilson (2018) shows is important.

Lindsay and Stein (2019) find that the availability of angel funding affects macro outcomes, such as the creation of new businesses and employment by small startup firms. They exploit the fact that the introduction of Dodd-Frank Act in the United States in 2010 implied a reduction in the number of accredited investors. Bernstein, Korteweg, and Law (2017) perform some randomized online experiments on AngelList, an electronic investment platform. They show that inexperienced angel investors react differently to information than more experienced angel investors. Our distinction between 'casual' and 'serial' angels builds on their categorization of investor experience.

The VC literature is much larger than that on angel investors. Da Rin, Hellmann, and Puri (2012) provide a comprehensive survey of that literature. Closest to this paper are the literatures on staged financing (e.g. Gompers, 1995; Tian, 2011), and independent versus corporate venture capital (Chemmanur, Loutskina, and Tian, 2014; Fulghieri and Sevilir, 2009; Hellmann, Lindsey, and Puri, 2008). Furthermore, our work is related to Ozmel, Robinson, and Stuart (2013), who examine the dynamic interactions between VC financing and strategic alliances.

The paper that considers both angels and VCs, and is the closest to ours, is Goldfarb, Hoberg, Kirsch, and Triantis (2013), who make use of a unique dataset from a bankrupt law firm that contains 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, a finding that is consistent with what we know from other research on VCs (e.g. Kaplan and Strömberg, 2003) and angel investors (Van Osnabrugge and Robinson (2000) and Wong (2010)). They also find a negative performance effect of mixing angel and VC funding and argue 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 complements the work of Goldfarb et al. (2013) in several important ways. We examine the full dynamic relationship between angel and VC funding, while their data only allows them to look at possible angels and VC syndications in the same round. We also exploit exogenous variation in available tax credits to address identification issues, and we are able to make finer distinctions amongst different types of angel investors.

Hellmann and Thiele (2014) provide a theory that explicitly models an aspect of the dynamic interaction between angels and VCs. In their model companies want to proceed from angel to VC funding. VCs may use their market power to squeeze out angel investors, which in turn encourages angels to seek out alternative exit routes. A key insight from the theory is that the bargaining dynamics between angels and VCs may determine whether the relationship is one of complements or substitutes.

Two more papers provide further useful theoretical foundations for comparing angels and VCs. Chemmanur and Chen (2014) assume a complements relationship in a model in which VCs add value, but angels do not. Their model explains why entrepreneurs might want to first obtain angel financing before switching to VC. Schwienbacher (2009) assumes that both angels and VCs can add value, but that only VCs have enough money to refinance a deal. This assumption also gives rise to a complements relationship between angels and VCs. Specifically, angels endogenously provide more value-adding effort, because of the need to attract outside capital at the later stage. However, this complements relationship would disappear if angels (possibly through co-investment) can provide follow-on funding. Some empirical studies suggest this has increasingly been the situation since the start of the millennium (e.g. Mason et al., 2016; OECD, 2016). In their Canadian study, Carpentier, and Suret (2015) conclude that "The classical funding escalator, including venture capitalists, no longer appears to be a dominant model." In a related vein, a study of

Californian early-stage financing by Chen (2018) notes that 70% of VC-backed companies did not have prior funding from angels or other external investors, also suggesting considerable separateness. Overall, the literature remains inconclusive about the relationship between angel and venture capital funding.

3. Data and variables

3.1. Data sources

Our primary data source is the Government of British Columbia, who administers the British Columbia Investment Capital Program (henceforth BCICP). The core of the program is a tax credit for qualifying BC investors of 30% of the amount they invest in the equity of eligible BC companies. Our analysis hinges on the special feature of the BCICP that this 30% tax credit applies to equity investments by both angel investors and VCs. Sandler (2004) shows that most North-American public policy initiatives target only VC, rather than the angel segment of the market.

Our BCICP dataset contains detailed company and investment activity information. To ensure compliance with the tax credit rules, all companies have to report their investments and ownership, for as long as they make use of the programme. Over half of the companies comply by simply submitting their entire share registry, which contain the entire history of the share issues to the individual investors in the companies. However, there are other ways to comply. The remainder of the companies thus provide information on their investments, investors, and ownership in a variety of other formats. This data submitted for regulatory compliance provides the basis of our analysis.

We augmented the BCICP data using several additional data sources. First, these sources helped us classify investors into types. Investors do not only include angels and VCs, but also other financial parties, corporations, as well as smaller parties such as universities, charitable organizations, etc. Secondly, as we are interested in how companies evolve and perform over time, we collected investor exit and company survival data from the BC company registry; Corporations Canada (the Canadian federal company registry); Capital IQ; ThomsonOne (VentureXpert, SDC Global New Issues and SDC Mergers and Acquisitions); Bureau Van Dijk (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", the record of filings with the Canadian Securities Administrators of public companies and investment funds; "EDGAR", the record of filings with the SEC; and the Internet (using mostly Google searches and an internet archive called the Wayback Machine (http://archive.org/web).

3.2. The British Columbia Investment Capital Program (BCICP)

This section contains a selective summary of the BCICP. Further detail is found in the Online Appendix, as well as in Hellmann and Schure (2010), Lerner, Hellmann, and Ilyaszade (2012), and Government of British Columbia (2017).

The BCICP was established in 1985 under the Small Business Venture Capital Act of British Columbia. By the end of our sample period in 2009, the BCICP has four segments that all offer a tax credit for BC investors worth 30% of the amount they invest in the equity of eligible entrepreneurial companies. The 30% tax credit is available to BC-resident individuals, as well as to corporate investors that have a "permanent establishment" in BC. Eligible companies under the BCICP are BC-based companies that, at the moment of registration, and together with affiliate companies, if any, do not employ more than 100 employees and contractors; that pay at least 75% of the wages and salaries to BC employees; and that "engage in an eligible activity", i.e. primarily R&D of proprietary technology, manufacturing, and digital media. BC securities legislation also imposes some rules on companies that issue securities in BC (see British Columbia Securities Commission, 2017). The Online Appendix contains more detail on the eligibility criteria for investors and companies.

The BCICP has four segments of which two target angel investors. The first consists of tax credits for investments in funds called Venture Capital Corporations. These should be thought of as angel funds that are structured as corporations, and we will therefore call them angel funds (ANF).[4] The second segment

[4] The name 'Venture Capital Corporation' is misleading, as these funds do not attract institutional investors, only private individuals. They are not professionally managed but are run by their investors themselves. Consequently, we consider them angel funds, which is also what the BCICP program managers consider them to be.

of the program is called the 'EBC program' which was introduced in April 2003. It consists of tax credits for non-intermediated equity investments into eligible companies. Since there is no need to set up an investment vehicle, the EBC program is administratively much simpler for angels than starting an angel fund. Indeed, the EBC program was intended to reach out to a wider set of angels. Eligible investors, including angels, can simply claim the 30% tax credit on the basis of an investment in an EBC.[5]

The other two segments of the BCICP promote VC investments made by what we call *retail venture capital funds* (RVCs). The two retail fund program segments are very similar. RVCs are all required to be professionally managed. They have the permission to approach investors from the general public, who again receive a tax credit of 30% of the amount they invest in an RVC. RVCs must have a prospectus when they approach investors and they must invest the funds they raise within a specific time frame into eligible companies. The two RVC programs only differ in how the 30% tax credit that they benefit from indirectly is funded. In the so-called Labour-Sponsored Venture Capital Program, the federal and provincial governments share the costs equally, while in the Provincial Retail Venture Capital Program the BC Government fully funds the tax credits.

3.3. Companies and investment rounds

There are three sources for our transactions data. The first are so-called share registries that companies submit to the BCICP, the second is the administrative database of the BCICP, and the third is VentureXpert, a commercial venture capital database. We believe that the combination of these data sources provides a rare opportunity to obtain data on a segment of the finance market that is notoriously difficult to observe. While it is impossible to obtain information on all investments, let us explain why we believe that this database is a significant step forward in the study of entrepreneurial finance.

A unique part of our data is the collection of share registries, which document investor identifiers, investment dates, number of shares, and the share price. These share registries often span the complete

[5] The eligibility requirements on investee companies are the same between the EBC and the angel fund segment of the BCICP.

histories of the share issues in the company, that is, they contain equity investments made before and after the companies registered under the BCICP, and both by investors who claim tax credits, but also those that do not (e.g. out-of-province investors). By contrast, the BCICP administrative database contains only the investment data made by BCICP-supported investors, but it gives the breakdown across the four segments of the tax credit program. Investment data found in VentureXpert cover investments by VCs and other investors such as corporate investors.

As our analysis concerns the dynamic financing path of entrepreneurial companies, we require all companies in the sample to receive a minimum of two financing rounds. We focus on companies whose first financing round took place after January 1995. Our sample runs until March 2009. Our sampling criteria generate a set of 469 companies that form our core sample. For 232 of those companies we have their share registries. In this case we augment the investment with the use of the administrative database and VentureXpert, to identify possibly investments made after the last date on the share registry. For the remaining 237 companies for which we do not have share registries we work with the BCICP administrative database and augment it with the information from VentureXpert.[6] One limitation of using the BCICP administrative database (as well as VentureXpert) is that we may not always be able to observe the transactions of some investors, most notably investors that do not claim any tax credit. The generous 30% tax credit is likely to be used by the vast majority of the investors, but some may not be eligible (such as investors from outside BC), while others may not make use of the program for another reason (see our discussion in the Online Appendix).

Our transaction data do not explicitly identify which share purchases belong to the same financing round. However, we do observe that many share purchases are recorded around the same date, presumably because they belong to the same financing round. We operationalize financing rounds by assuming that all investments made in the same quarter are part of the same financing round. When companies raise funds

[6] Note also that there are 101 companies in VentureXpert that satisfy our sample criteria, of which 91 are also in the BCICP dataset. For those we augment the BCICP data with VentureXpert data. We drop the remaining 10 companies that are only in VentureXpert, given the concern that we do not have any information about their financing history prior to obtaining venture capital.

during a time span that crosses two or more quarter boundaries, we adopted the following rule regarding the definition and timing of the financing round. The timestamp on a round is the quarter in which the first of a series of investments takes place. Subsequent investments are considered to be part of the same round if they take place within ninety days of a prior one.[7]

As part of our analysis we look at the eventual exit outcome of companies, distinguishing between those who have a successful exit, those that are still alive, and those that failed. Any company with an IPO is considered a successful exit. For companies that get acquired there is an empirical challenge to distinguish proper successes from disguised failures. We adopt the following procedure. If we know the acquisition value, then we consider an M&A successful if the acquisition value lies above the total amount of investment. If the acquisition value is not known, we consider it a successful M&A if there is some kind of press release with substantial and positive praise of the acquired company. We infer unsuccessful M&A as those where no press release is available, or if available, has little detail about the acquired company (e.g., just the name and a short factual description without praise). Specifically, we carefully went through all available press release of the M&A exits. Based on the press releases, we categorized the 102 M&A exits into 86 positive and 16 negative M&A exits. The positive M&A exits are grouped together with the IPOs companies and are treated as successful exits in our analysis. The negative M&A exits are grouped together with the failed companies, which also include companies that were not involved in an IPO or M&A, but are reported as no longer in operation according to the company registries of BC (provided by *BC Online*) or Canada (*Industry Canada*). While imperfect, we consider this method reasonable, and the best we can do with the limited data we have.

Our final sample contains information on 18,925 investments by 9,424 unique investors in 469 companies. The investments comprise 2,184 financing rounds.

[7] As part of compensation, founders and other company insiders sometimes receive shares for nearly free or have the opportunity to purchase shares in their companies at deeply discounted values ("sweat equity"). Our analysis aims to detect the dynamic logic behind investments in companies, rather than director or key employee compensation. We therefore remove all sweat equity transactions. Specifically, we remove all transactions in which shares were acquired for $0.01 or less and/or those for which we observed the shares were acquired for 10% or less of the share price paid by other investors in the same round.

3.4. Investor classification

As discussed in OECD (2011) there is no universally accepted definition for an angel investor, and what distinguishes an angel investor from a VC. Our definition of an angel investor is based on the distinction between direct versus intermediated financing: an angel investor invests their own (family's) wealth, whereas a VC invests on behalf of other funding providers (individual and institutional). We know from the literature that investors who invest their own money face different incentives and constraints than investors who are intermediaries that act on behalf of others (e.g. Diamond (1984) and Axelson, Strömberg and Weisbach (2009)). However, in the data we have an interesting borderline case, namely "angel funds". Angel funds involve a degree of financial intermediation, seeing that the investment functions of screening projects and negotiating terms are often delegated to a small management team of lead individuals. Yet, when we observe that these lead individuals also invest their own funds in the investment vehicle, we classify such funds as "angel funds", hence angels.

More generally speaking we adopted a two-step approach to classify our investors into investor types. In step 1 we separated investors into two groups, namely humans (7,015 investors) and vehicles (2,409). Human investors are identified by having only a first and last name (i.e. there are no additions like "Inc.", "Company", "Trust", etc.); vehicle investors are the remaining ones. In Step 2 we performed several name-based matches with other data sources to classify the vehicles into the type categories. In Step 2 we identify an investor as a VC if their name matches with any of the VCs in the Capital IQ and VentureXpert (ThomsonOne) datasets, or if a web search reveals that the vehicle is a fund, which "credibly" self-declares to be a venture capital fund. Credibly includes the criterion that it is managed by a team of investment professionals. The logic here is that professional investors purely invest on behalf of others. We thus identified a total of over 454 VC firms in our dataset, most of which through VentureXpert. The details of Step 2 are found in the Online Appendix.

Our principal categorization thus distinguishes Angels, VCs, and Other Investors. In the tables of the paper we abbreviate these investors types as AN, VC, and OI, respectively. For some of the analysis in this paper we use a more granular investor categorization, which is introduced in Section 7 below.

3.5. Descriptive statistics

A description of all our variables is provided in Table 1. Table 2 reports descriptive statistics at financing round and company levels. Panel 2A shows that of the 2,184 financing rounds 1,491 (or 68.3% of the rounds) involved one or more angels, 690 (31.6%) one or more VCs, and 798 (36.5%) one or more Other Investors.

Panel 2A presents boxes with other descriptive statistics on investment rounds. The second box shows how many companies receive just angel, but no VC financing; how many receive no angel, but VC financing; how many receive funding from both angels and VCs; as well as how many companies receive funding from neither angels nor VCs. We note that syndications between Angels and VCs are “rare” in the following sense: if investor types would mix randomly over the rounds, then angels and VCs would syndicate in exactly $0.683 \times 0.316 = 21.6\%$ of all 2,184 rounds. However, the data show that angels and VCs actually co-invested in only 6.9% of the rounds.

The next box of Panel 2A shows that in an average round angels, VCs, and Other Investors invested \$240K, \$1M and \$210K, respectively. Not surprisingly, angel rounds are much smaller than VC rounds. Moving down we learn that the median age of companies is 1.0 years at the time of their first financing round, while the average age at the first round is 2.4 We observe companies’ financing history for an average of 3.8 years after their first round. Companies are hence on average 2.4+3.8=6.2 years old at the time of the last financing round we observe. Companies tend to be slightly older in VC rounds, yet the age statistics are of the same order of magnitude across angel, VC, and Other Investors rounds.

Our analysis focuses on the evolution of investor types. Our regression analysis will therefore focus on follow-on rounds (i.e. rounds other than the first rounds of our companies), because prior investor types can only be defined for follow-on rounds, not for first rounds. An interesting distinction for these follow-on rounds is between insider rounds, that are funded entirely by existing investors that already invested before, versus outsider rounds that include a least one new investor that did not yet invest before in the company. The penultimate box of Panel 2A provides some data on these follow-on rounds. For example, we find that 56.3% of the follow-on rounds involve at least one new angel investor, and 29.0% at least one new VC. Interestingly, 14.9% of follow-on round involve no new investors, i.e., they are pure insider rounds.

The last box of Panel 2A shows that the time between rounds is very close to one year, with minor (and statistically insignificant) differences across the investor types.

Panel 2B shows descriptive statistics at the company level. The first column shows statistics that reflect the observable lifetime of our 469 sample companies. The second and third column show statistics for two subperiods of a company's life called the `early period' and `late period'. Here the early period, is defined as the first two years of the company lifetime, and the late period the time thereafter. Note that 447 of the 469 companies in our sample reach the age of two.

A first thing that stands out is that angels are the most common financiers at the company level as well. No less than 84.4% of the companies receive angel financing at some stage in their life (54.8% of our companies receive angel financing in the early period; 69.1% in the late period). The next box in Panel 2B categorizes the companies into four mutually exclusive subsets: those that receive just angel, but no VC financing; those that receive no angel, but VC financing; those that receive both angel and VC financing; and those that receive neither angel nor VC financing (so only from Other Investors, who may be present in the first three categories as well of course). In the early and late periods there is a fifth category of companies, namely those that did not receive any funding at all, because no round took place during the period.

The following box in Panel 2B reports average funding amounts, revealing again that VCs invest larger amounts. For each investor type we see that much more funding is invested in the late period than in the early period. The box below shows the distribution of our companies over industry sectors and regions. Our industry classification is loosely based on NAICS codes, where we focused on innovative companies.

The necessary information on the companies' activities was taken from their BCICP registration applications (which include business plans in the majority of the companies), as well as internet searches. Most of the BCICP companies are active in the software industry (28.1%), Hi-tech manufacturing (17.9%) or biotech (12.2%). Taken together, high-tech companies account for 76.5% of the companies in our data, while the other 23.5% of companies focus on Art, Recreation and Tourism ("Tourism") or Agriculture, Forestry, Fishery, Mining, Construction, or Non-high-tech manufacturing (designated for export) ("Other"). These last two categories are eligible under the BCICP (outside the two main urban areas) because they are deemed to further the government's objective to "enhance and diversify the BC economy" (Government of British Columbia, 2017). The industry distributions of angel, VC, and Other Investors rounds are roughly the same, although VCs may be found somewhat more frequently in Biotech, and less frequently in High–tech services and tourism.

The location distribution (again from the BCICP data, and, in a few exceptional cases, internet searches) shows that the majority of our companies are concentrated in and around Vancouver – 72.9% of them are located in the Greater Vancouver Regional District.[8] The two smaller hubs for innovative activities are BC's Capital Region District ("Greater Victoria"), and, in the East of BC, the adjacent areas of the Okanagan and the Thompson River Valley.

Panel 2C shows data about the investor type categorization and draws the link between investor types and funding at the company level. We learn that our 9,424 unique investors consist of 7,215 Angels, 454 VCs and 1,755 Other Investors. Columns 1 and 2 of Panel 2C reflect the first financing round of our companies. Observe that 70% of the first rounds involved one or more angels, compared to 25% and 46% for VCs and Other Investors. Column 2 shows that if a VC was involved in the first round, then the first-round average VC funding amount is $2.3M. This figure is higher than for angels, who invest on average $440K in first-rounds where they are present, and Other Investors, who invest on average $590K in first rounds in which they are present. Columns 3 and 4 aggregates over all the investment rounds, and hence

[8] 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.

shows the per-company averages. The per-company average investment amounts was just over $7M. Conditional on their presence in any round, angels invest on average $1.32M, VCs $13.43M, and Other Investors $1.73M.

Panels 2D through 2G provide descriptive statistics regarding the dynamic evolution of investor types. Each of these four panels shows transition probabilities of going from one of the four mutually exclusive states (Angel and No VC, No Angel and VC, Angel and VC, No Angel and No VC) to another. Panel 2D shows the data from the first round to the end of sample, hence describing the transition matrix for the first round to what happens during any of the rounds during the lifetime of the company. Panel 2E shows the transition between consecutive rounds, hence focusing on whether a company had any angel and/or VC funding in individual rounds. Panels 2F and 2G show transitions from early to the late period in the life of companies. Panel 2F is based on all investor-types that invested in the late period, that is, including investors that invested in the early period as well. By contrast, Panel 2G only counts investments in the late period made by new investors, that is it excludes investors that had also invested in the early period.

Two main messages emerge from Panels 2D–2G. First, there is a strong persistence-within-investor-types, something that we will confirm in the regression analysis. Second, despite this persistence, there remains a substantial amount of change over time. This last message can perhaps best be seen from Panels 2E, 2F and 2G, which all show that for all investor-compositions of companies there are transitions to *each* of the four investor compositions in future rounds-periods.

Panel 2H provides data on the company's exit status in August 2018. We searched in *SDC Mergers and Acquisitions*, *SEDAR*, *CapitalIQ*, *LexisNexis* and the Internet to check whether companies were involved in IPOs or acquisitions. We also consulted the BC and Canadian corporate registries to learn about the status of the remaining companies. (BC based companies can choose whether to incorporate provincially or federally. The corporate registries are quite reliable indicators whether companies are still alive as companies are removed from the corporate registry unless they file their financial statements annually.) In August 2018, 23% of our 469 companies had exited through either an IPO or an acquisition, and 50% of them had failed.[9] The remaining 27% of the companies in our dataset were still active. An interesting question is how performance relates to a company's investor types. As Panel 2H shows, exit rates vary substantially with investor composition .

Finally, Panel 2I reports pairwise correlation coefficients between some of the main variables of interest at the company level. There are negative correlations between the various measures of angel and VC funding.

4. Dynamic funding patterns

4.1. Empirical specification

Our study of the investor dynamics focuses on the relationship between investor types in the current round and prior investor types (from all earlier rounds). Our unit of observation is therefore the financing round (denoted by the subscript r). We follow our sample companies from their first to their last round. However, in the first financing round of a company (r=1) there are no prior investors, so that our sample effectively begins with the second round. This is not merely a technical necessity but reflects our fundamental research question of how companies dynamically progress from one type of investor to another. Our main round to round regression model is as follows:

$$J_{ikr} = \alpha + \sum_k \beta_k I_{ik,r-1} + \gamma X_i + \delta X_{ir} + \eta_t + \varepsilon_{ikr}$$

The dependent variable, J_{ikr}, is an indicator variable for whether company i obtains any funding from investors of type k, in round r. Our regression specification does not reflect a single equation, but rather of an equation for each investor type. We initially consider three types, Angel investors, VCs and Other Investors, and we disaggregate these three investor types into seven subcategories later in the analysis. We

[9] A general concern with M&As is that they could include some hidden failures. To address this concern, we examined all available press releases associated with all M&As in our sample (102 companies). We specifically look for indications of hidden failures including lack of "praise", lack of substantial mentioning of the acquired companies (i.e. our sample companies) in the press release, unavailability of press release, etc. Through this exercise, 15.7% of the M&As in our sample are determined hidden failures. These M&As are thus classified as failed companies in our data. The remaining 84.3% of the M&As are classified as exited companies in our data.

use two specifications for J_{ikr} throughout the analysis. In the "new-investor" specification J_{ikr} switches to 1 only in case one or more new investors of type *k* invested in the round. By contrast, the "all-investor" specification counts both existing and new investors. The "new-investor" specification provides a more stringent test of the dynamic relations between investor types, as repeat investments of individual investors are excluded by design. It thus measures the persistence of investor types, as opposed to persistence of specific investors over time. We report both specifications in our empirical results to get the complete picture.

The most important independent variables are $I_{ik,r-1}$, k=1,…,3, which are indicator variables for whether company *i* had any investors of type *k*, up to and including round *r*-1. This variable keeps track of what investor types are already present in the company just before the current round.

In terms of controls, X_i is the set of variables that measure all time-invariant company characteristics, namely: company age at the time of the first round, industry, and location. We report those controls in Table 3 below, but omit them in all subsequent tables to save space. X_{ir} are time-variant company characteristics, namely (i) the total amount raised in all previous rounds, (ii) the time since the first round (measured non-parametrically with a complete set of dummies for each quarter), (iii) the time since the last round (measured non-parametrically with a complete set of dummies for each quarter, restarting the counter every time a new round occurs), and (iv) a dummy control for whether the round data were obtained from the company's share registry (dummy = 1) or from the BCICP database and VentureXpert (dummy = 0). Our non-parametric time-controls, (ii) and (iii), are included to capture possible independent time-varying factors, allowing us to isolate the relationship between prior and current funding choices.[10] Finally η_t are a complete set of calendar-time fixed effects. These control for any seasonal effects, any business cycles effects, or indeed any other calendar time effects. All our regression models use these controls, but for the sake of brevity they remain unreported in the results tables.

[10] 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 the same results.

Throughout the paper we use OLS regressions with robust standard errors, clustered at the company level; we denote these by ε_{ikr}. Of course, we recognize the possibility that unobserved heterogeneity creates a possible correlation between the error term and the dependent variable, which is commonly referred to as the endogeneity problem. In this section we report the results without any endogeneity correction, but Section 5 explicitly focuses on issue of unobserved heterogeneity.

4.2. Results from the round to round model

Table 3 shows the estimation results of our round to round model. Columns 1-3 report the results of the three "new investors" regressions, namely new angel investors (New AN), new VCs (New VC), and new Other Investors (New OI), respectively. Columns 4-6 show the all angel investors (All AN), all VCs (All VC), and all Other Investors (All OI) regressions, respectively, that also count investments by repeat investors for setting the investor type dummies.

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) are always positive and strongly significant at the 1% level. This suggests that companies that have already received funding from one type of investor are likely to receive further funding from that same investor type. Importantly, this result is *not* driven by repeat investors, since our dependent variable in Columns 1-3 only measures investments from new investors.

Our most interesting finding concerns the negative relationship between angel and VC funding. If company received prior angel funding, it is less likely to raise VC funding, and conversely if a company received prior VC funding, it is less likely to raise angel funding. Both these off-diagonal coefficients are statistically significant at the 1% level. This finding suggests a dynamic financing pattern of 'substitutes' between angels and VCs.

Table 3 also shows that prior funding by other investors is associated with a lower probability of VC funding, and prior angel funding with a lower probability of other investor funding. In addition, it shows some interesting and intuitive patterns for the control variables. For example, VC funding is less prevalent outside of the main urban centres of BC, and in certain industries such as high-tech services or tourism.

It is worth pointing out that the economic magnitudes appear large. Since we only use linear regressions, the coefficients can be interpreted directly. For example, in Column 1 of Table 3 the prior presence of angel investors increases the probability of obtaining new angel investors by 30.0%, whereas the prior presence of VC investors decreases the probability of obtaining new angel investors by 24.6%. In Column 2 the magnitudes are even higher, the prior presence of VC investors increases the probability of obtaining new VC investors by 30.0%, whereas the prior presence of angel investors decrease the probability of obtaining new VC investors by 34.7%.

We also considered a permutation of the round to round model where instead of using dummy variables indicating the presence of investor types (both as dependent and independent variables), we used log investment amounts by investor type. We find that the pattern of results is very similar, details are reported in the tables of the Online Appendix.[11]

4.3. Alternative specifications

The round to round model has the advantage of focusing on the funding moments of companies. However, this is not the only reasonable choice of sample when studying the dynamic interaction between investors. In this section we consider several alternative specifications.

One potential concern might be that our results are impacted by a situation in which different investor types tend to have different investment frequencies. Panel 2A, for example shows that there is slightly more time between VC rounds (4.3 quarters) than between angel rounds (3.9 quarters) (although the t-test for the difference is not statistically significant). We want to verify that our results, such as our finding of relatively infrequent switches between angel and VC financing, are not driven by differences between investors in the number of rounds, the time between rounds, etc. For this purpose, we estimate a

[11] Syndication between angels and VCs is an issue closely related to our analysis. In Section 3 we already noted that syndicated rounds of angels and VCs are relatively rare. To further examine the determinants of such syndicated financing rounds we reran our round to round model using syndicates (i.e., investments containing both angels and VCs) as a dependent variable. The results are reported in the Online Appendix. The main finding is that syndicated deals can arise from both from prior angel funding as well as prior VC funding, with neither of these two sources dominating the other. Moreover, there is a strong persistence in syndication, in the sense that companies who already have both angels and VCs are particularly likely to attract new investors of both types in future rounds.

second empirical model that is based on the cross-section of companies, and therefore independent of such possible differences between investor types. Yet, the idea behind this second empirical model is again to ask how the choice of investors later in the company's life relates to the investors early in the life of a company.

For our main *early to late model* we count the first two years as the early period, and all subsequent years as the late period. The tables of the Online Appendix contain three robustness checks based on alternatives for where to draw the line between the early and the late periods of companies. However, all variations of the early to late model look as follows:

$$J_{ik} = \alpha + \sum_k \beta_k I_{ik,} + \gamma\, X_i + \eta_t + \varepsilon_{ik}$$

Here the dependent variable, J_{ikr}, is an indicator variable for whether company *i* obtains any funding from new investors of type *k*, in the late period. This is a function of the indicators I_{ik} for whether company *i* obtains any funding from investors of type *k* in the early period. The other variables are essentially the same controls as used in our round-to-round model.

Table 4 reports the results from the early to late model. Observe Table 4 is based on the 447 of our 469 companies who reach the age of two years and therefore have an early and a late period. The results in Table 4 are broadly in line with those of Table 3. Specifically, we find negative and highly significant coefficients for the transitions from early angel to late VC investments, as well as from early VC to late angel investments. The persistence from early VC to late VC also remains strong. The main difference with Table 3 is that the coefficient of early angel to late angel investments is now insignificant. There are also some differences with respect to other investors, such as the negative and significant coefficient of early VC on late other investors. Note also that the new investors model (Columns 1-3) and all investors model (Columns 4-6) produce again very similar results.

The early to late model neutralizes the possible effects of companies having multiple rounds or a difference in the round frequencies between angels and VCs by reducing the sample to the cross-section. An alternative approach would be to turn the sample into a balanced panel, in which the unit of observation is not the round (which may happen irregularly), but a regular time period. Specifically, we also consider quarterly periods, and ask for every quarter whether the company raised any funding from an investor type during the quarter. This sample therefore contains all company-quarters, independently of whether a funding round occurred. We report the results in the Online Appendix. The empirical results are again in line with the results from Table 3.

To further test the validity of our main model from Table 3 we finally perform a simulation. The goals are to establish the validity of our round to round model, to assuage any potential concerns that the patterns in the data might be a mechanical implication of any staging of financing, and to show the connection between the estimated coefficient and the concepts of substitutes / complements.

Our simulation exercise is based on the same sample size of 469 companies and we leave their funding round structure intact. In a first baseline step we ask whether in a world in which there is no persistence of investor types (i.e., neither a substitutes nor a complements relationships between angels and VCs) we might mechanically find the actual results of our paper. Thus, in each round investor types are drawn randomly. Specifically, each investor type occurs in a round with a probability that corresponds to the investor type frequencies in our data. After populating the rounds in this fashion, the model coefficients are estimated. We find for the baseline model that none of our simulated coefficients are significant.

The second step of our simulation exercise is to stipulate the simplest possible model of persistence within investor types. We model this by assuming that once a company has been given an initial random investor type, its probability of subsequently receiving new investors of the same type increases by some percentage. We call the parameter of own type persistence α. In our simulation trials we consider various values for α. We find that an increase in α increases the estimated coefficients on the main diagonal in the simulated regression. However, importantly, α does not materially affect the estimated coefficients off the main diagonal. This is consistent with our interpretation of the positive coefficients on the main diagonal of Table 3 as representing persistence within investor types.

The third step of our simulation exercise is to stipulate the simplest possible model of interactions between the investor types. We focus on the relationship between angels and VCs. Specifically, we assume when generating the round data in our simulation trials that once a company has received funding from a randomly drawn investor type (AN or VC), the probability of subsequently attracting funding from the other type either increases (in the case angels and VCs are complements) or decreases (substitutes) by some percentage β. We again consider a variety of parameter values for β and find that positive values of β generate positive estimated off-diagonal coefficients for the angel – VC interaction effects, while negative values of β generate negative estimated off-diagonal coefficients for the angel – VC interaction effects. This finding is obviously in line with our interpretation of the negative coefficients in Table 3, which we take as evidence for a substitutes relationship. We also find that changes in the parameter β does not materially affect the main diagonal. The Online Appendix presents the details of the simulation study.

5. Investor-led versus company-led interactions

5.1. The identification challenge

The analysis so far allows us to distinguish whether two investor types are in a substitutes or a complements relation. The next question is whether new investor choices are led by the existing investors or rather by the companies. As discussed in Subsection 2.1, this is closely related to the empirical question of whether the correlations observed in Table 3 are due to selection or treatment effects.

The empirical challenge is to find some exogenous variation in the data that separates these two effects. We first note that it would not be enough to consider shocks to the overall funding availability in the market, because our research question pertains to choices across different investors within the market. Instead we need to look for exogenous shifts in the *relative* availability of alternative financing types. In an ideal scenario the government would have differentially changed the rates at which tax credits are made available to angels and VC investments. Unfortunately for us the tax credit rate has remained fixed at 30% of invested amounts over time and for all investor types. However, the provincial government did make shifts in tax credits amounts across the different program segments over time. A noteworthy example is the introduction of the EBC program in 2003 (see Section 2.2) which favored direct investments by angels. We thus take an instrumental variable specification that exploits the historic variation in the amounts of tax credit across different program segments.

Recall from its description in Section 3.2 that the BCICP targets individual angel investors (the EBC segment), angel funds (ANF), as well as Retail VCs (RVC). For each of the EBC, ANF and RVC program segments we observe the annual amount of tax credits disbursed. The variable that we want to instrument for is the prior investor types of companies. The idea for the instrument is that the prior choices about investor types are influenced by the past availability of tax credits. Prior investor choices occur over different periods of time for different companies, so we use a company-specific weighted average of our tax credits availability measure. For the weights we use the company's past investment amounts as a percentage of its cumulative investment amount. This way the weights reflect those past time periods when the company was actually raising funds.

The conceptual foundation for our instruments is that differential access to tax credits should have a direct effect on the funding provided by alternative investor types. This is the rationale for satisfying the rank condition. The exclusion restriction in any IV estimation cannot be tested empirically. Instead it relies on a theoretical rationale for why the instrument should have an indirect, but not a direct effect on the variable of interest. Our argument is based on a simple logic of time lags. Specifically, tax credits available in the past cannot have a direct impact on current investment choices. This is because tax credits only apply in the current year, not in future years. The availability of tax credits in past years is therefore also of no direct relevance for investor choices in the present. However, past tax credits could affect current investor choices indirectly, through their impact on investor choices in the past, which we know from our study, may affect current investor choices. This indirect effect is in fact the channel of transmission postulated by our instrument. Indeed, the point of the exclusion restriction is that while the instrument (past tax credits) should not have any direct effects on the dependent variable (current investor choices), it has an indirect effect via the channel of the instrumented variables (past investor choices). The availability of tax credit generates three instruments, one for every major segment of the tax credit program.

Going one step further, one may argue that what matters the most is whether a certain tax credit program is available or not. While tax credits for retail VCs and angel funds were available throughout the sample period, this was not the case for tax credits through the EBC (individual angel) program. The EBC program took effect on April 1, 2003 and was put on hold in the 4th quarter of 2007 because tax credits had run out. Our fourth instrument is therefore based on what fraction of time in a company's past the EBC tax credit was actually available.

Apart from tax credits, companies benefit more generally from possible supply shocks in the availability of funding. In our context we can measure total supply of funding by investor classes over time. Thus, our measures capture the activities of all investors of each investor type, not just the activities that benefit from tax credits. Our logic is closely related to the seminal paper by Berger et al. (2005) which uses exogenous changes in local market conditions as an instrument for the availability of different types of capital. That same logic has since been used in numerous venture capital studies (Da Rin et al., 2012).

To construct the instruments, we use the same company-weights as with the tax credit measures. However, the supply measures are constructed on the basis of investor segments (Angels, VC, and Other investors), not program segments (EBC, ANF, and RVC). This approach generates three more potential instruments, one for each investor type.

5.2. Instrumental variable regressions

Table 5 reports one of the three first-stage regressions.[12] It shows that an increase in the tax credits in the RVC program is associated with significantly higher likelihood of VC funding, and significantly lower probability for Other Investors. More tax credits in the ANF budget has the opposite effect and is associated with a significantly lower probability of VC funding, but a significantly higher probability for Other Investors. More EBC funding is associated with a higher probability of angel investments. Moreover, the availability of EBC funding is positively related to investments from both Angels and Other Investors.

[12] In the upper panel of Table 5 we report the first-stage regression for the estimation of the 'New AN' regression reported in first column of the lower panel. The first-stage results for the second and third column regressions are very similar.

All these results are consistent with the intended functioning of the tax credit program. The coefficients of the three "investor-type instruments" are mostly insignificant.

To test our identification approach, we use a standard Chi-square test to assess the strengths of the instruments in the first stage. The Chi-square test for the joint significance of the instruments indicates that they are always jointly significant, with p values in the 0.00 to 0.07 range. Nonetheless, we acknowledge that our instruments are not overly strong, and therefore consider our identification analysis indicative, but not conclusive.

In the second stage regressions, the main finding is that none of the key coefficients are statistically significant. We cannot exclude the possibility that the lack of significance is partially driven by our weak instruments. Yet, the results tentatively suggest that the correlations in Table 3 are based on unobservable selection, rather than treatment effects. This is more consistent with the company-led substitutes hypothesis ('parallel stream') than the investor-led substitutes hypothesis ('sink holes').[13]

6. The relationship between investor choices and performance

6.1 The quality-contingent complements hypothesis

In this section we consider one important alternative explanation for the substitutes patterns observed in Section 3. Put simply, under this alternative hypothesis VCs and angels are in fact complements, but only for the good companies. The reason to look at this *quality-contingent complements hypothesis* is a possible concern that the 'parallel streams' finding might arise because of a large number of bad companies that remain stuck with angels, and a limited number of good angel-backed companies that 'graduate' to VC funding.

To empirically evaluate the quality-contingent complements hypothesis, we ask whether the negative relationship between angel and VC funding holds true across the performance spectrum. Under

[13] To address potential concerns that the tax policies alter the composition of start-up companies seeking funding in BC, we did a robustness check in which we reran the model by dropping all first two rounds. One would expect potential composition effects to matter the most in the early stages. However, our empirical findings are very similar, alleviating concerns about a changing composition of firms.

our ‘parallel streams’ hypothesis we would expect the substitutes pattern to hold across the entire performance spectrum, whereas under the quality-contingent complements hypothesis one would expect the substitutes pattern to switch (or at least disappear) for the higher performing companies.

We will proceed in two steps. In Section 6.2 we first ask whether there is any quality sorting in the data. We will find evidence that suggests that VCs match with better performing companies, consistent with the notion of quality sorting. However, this by itself does not establish the quality-contingent complements hypothesis. That is why in Section 6.3 we ask whether the substitutes pattern changes for high quality ventures. Our empirical evidence will not support this hypothesis.

One practical empirical challenge is that performance is hard to observe in privately held companies. The approach we use is based on exit performance, an ex-post outcome measure. There is a large prior VC literature that uses exit outcomes as a proxy for performance. This approach was validated by the work of Phalippou and Gottschalk (2009). In our data we can classify companies into three distinct categories: (i) those that ultimately experienced a successful exit event, as measured by a successful acquisition or IPO; (ii) those that are still alive by the end of the sample period; and (iii) those companies that failed. We will thus ask whether the substitutes pattern observed in our round to round model holds across these different subsets of companies.

6.2 Investor types and performance

In this subsection we look for evidence of quality sorting, examining the relationship between investor types and company performance. Table 6 reports the results from linear regressions at the round level that examine the relationship between investor types and performance. Columns 1 and 2 present what we call an ‘augmented round-to-round sample’. In addition to the usual financing rounds we add a final observation per company that represents its ‘outcome’, namely exit, alive, or failure. *Exit* is a dummy variable that is zero in all rounds, but the “outcome round” in which it takes on the value of one if and when the company exits through either an IPO or a ‘successful acquisition’ (as defined in Subsection 3.3). *Failure* is a dummy that becomes one in the outcome round if the company had failed by August 2018. For companies that are still alive by August 2018 both the exit and failure dummy remain at zero in that outcome round. Columns 3 and 4 are based on the cross-section of companies. Here we regress the two outcome dummies on the investors the company attracted during its observed lifetime. In the regressions of Table 6 we always include our standard control variables.

None of the investor type coefficients of Column 1 of Table 6 is significant. However, the VC coefficient is positive, the angel coefficient is negative, and we can show that the difference between these two coefficients is significant at the 1% level. Thus, VCs are associated with better performance in terms of successful exits than angels. Column 2 shows a positive relationship between angel investments and failure that is significant at the 10% level. The coefficient on VC is negative, and the difference between the two coefficients again turns out to be significant at 1% level. This means VCs are associated with better performance than angels in this regression as well. Columns 3 and 4 show that VCs are associated with more exits and fewer failures than angels. In both columns the coefficients associated with VC and angel financing are significantly different at the 10% level. In Column 3 the VC coefficient is also significantly different from zero at the 5% level.

The central finding of Table 6 is that VC financing is associated with stronger company performance than angel finance. VC-backed companies have more exits, and fewer failures than angel-backed companies. These findings are consistent with prior studies – see the VC literature survey of Da Rin et al. (2012). In our sample VC-backed companies have a 27% higher probability of exit and a 18% lower probability of failure than angel-backed companies.[14] These results reflect correlations, not causality. As Da Rin et al. (2012) explain further, a large prior literature tries to disentangle selection and treatment effects for the effect of investors on performance. We reran the regressions of Table 6 using the instrumentation behind Table 5. The results are reported in the Online Appendix. They show that none of

[14] We also ran the augmented round to round model of Table 6 adding an interaction dummy indicating prior angel and prior VC funding. The results are shown in the Online Appendix. Interaction terms play an important role in Goldfarb et al. (2013). In our setting the coefficients for the interaction terms are always insignificant.

the investor-type-coefficients are statistically significant, suggesting the relationship between investor types and performance reflects a selection effect.

6.3 Substitutes across the performance spectrum

The evidence in Subsection 6.2 supports the presence of quality sorting, a necessary condition for the quality-contingent complements hypothesis. We now investigate the quality-contingent complements hypothesis. Specifically, we ask whether angel-backed companies with a strong performance are prone to switch to VC. If this were the case, the substitutes pattern should reverse (or at least weaken) at the high end of the performance range.

In Table 7 we rerun the round to round model of Table 3 and the early to late model of Table 4 on two subsamples, namely (i) companies that had a successful exit, and (ii) companies that went out of business. Panel 7A shows that the coefficients of interest are essentially the same as for the full sample and they also retain their statistical significance. Panel 7B shows that the main coefficients of interest also remain the same in the early to late model. In fact, the coefficient of early angel financing on later venture capital financing is more negative in the subsample of companies with a successful exit than in the subsample of companies that failed.

Both the round to round and the early to late models suggest that the dynamic substitutes pattern does not seem to vary across the performance range of companies. In particular, there is no evidence that the negative relationship between prior angel funding and current VC funding disappears, let alone reverses, for companies that eventually have a successful exit. While the evidence of Subsection 6.2 shows that better companies are more likely to match with venture capitalists, Table 7 makes clear that this does not mean that better-performing angel-backed companies are more prone to switch to VC financing at later stages. Instead the evidence suggests that angel-backed companies are likely to remain within the angel stream, irrespective of whether they perform well or not. In sum, we find no evidence for the quality-contingent complements hypothesis.

One potential limitation of the approach of controlling for company quality taken in the regressions of Table 7 is the use of ex-post outcomes (i.e., successful exits and failures) to define the subsamples. This approach is justifiable if ex-post outcomes are correlated with unobservable information that the investors have at the time of investment. Still for robustness we also run a model in which we control for performance using company revenues. This is a fundamentally different approach from using exit performance, because revenues indicate current performance and are observable to investors at the time of the investment. Moreover, revenues are widely considered key metric of start-up performance, as it indicates development progress and the ability of a company to deliver something that the market wants. A potential drawback of using revenues is that these reflect a company's current performance and not necessarily the private information investors may have about the company's future potential. In our case a practical limitation of using revenues is that we could only collect revenue data over time for 289 of our 469 companies, or 982 of the in total 1715 observations in the financing round sample. We again rerun the round to round model on two subsamples, namely rounds associated with above-median revenues and rounds associated with below-median revenues. In both these subsamples the results are again similar to those in Table 3, which again suggests the quality-contingent complements hypothesis does not hold. The details are presented in the Online Appendix.

7. Investor subtypes

7.1 Definition and descriptive statistics

Our analysis of the dynamic financing pattern of small entrepreneurial companies has so far hinged on three investor types: Angels, VCs and Other Investors. In this section we disaggregate these categories further to obtain a deeper understanding of the interrelationship between different investor types. The more granular categorization allows us to (i) gauge the dynamic financing patterns within investor types, and to (ii) examine how cross-investor-type effects may vary by subcategories. Indeed, the biggest question is whether the negative relationship between angels and VCs applies uniformly across angel types.

We subdivide angel investors into three types.[15] *Casual angels* ("AN - CASU" in our tables) are involved in just a single company in our company dataset, albeit possibly in multiple rounds. *Serial angels* ("AN – SERI") in our dataset invest in more than one company. *Angel funds* ("AN – FUND") represent investment vehicles that are owned by more than one angel. VCs are subcategorized into *Private VCs* ("VC – PRIV") and *government-supported VCs* ("VC – GOVT"). Such government-supported VCs include the Retail VC funds that are described in Section 3.2, as well as those that are supported by the Business Development Bank of Canada. Recall that Other Investors form a quite diverse group. We split them into two categories. The first consists of founders, their family members, and key company employees ("OI – FOFA"), the second contains a variety of corporate entities ("OI – CORP"). The Online Appendix describes in detail how we scored our investors across the subcategories.

The logic behind the VC and Other Investors subcategories are fairly self-explanatory but let us briefly comment on the economic motivation behind the chosen angel subcategories. Serial angels are likely to be more experienced and committed to angel investing in the long term than casual angels. For example, it is likely that our casual angel category includes 'friends' who invest in a single company on the basis of personal relationships but have no intention to systematically engage in angel investing. Angel funds may behave differently from both casual and serial angels. Prowse (1998) distinguishes between "active" and "passive" angels within angel funds. He argues that active angels are more experienced and further develop relevant skills and networks in this position. In addition, angel funds are likely to have deeper pockets than individual angels. Angel funds may therefore become a viable alternative to VC funding for companies that require large investment amounts.

From Panel 2C we know there are 9,424 unique investors that consist of 7215 Angels, 454 VCs and 1755 Other Investors. Panel 8A shows that the bulk of our 7215 angels are casual angels (6801 casual

[15] Bernstein et al. (2017) categorize different angels on the bases of their "level of experience (measured by the number of investments), past success, or reputation (measured by the number of followers, or the weighted number of followers on the platform)." The approach we take in this paper is similar in spirit, but more constrained in terms of data. Specifically we also use the first criteria of number of investments (casual angels invest only once, serial angels invest more than once). However, we have no data on past successes or reputation.

angels), while there are 214 serial angels and 200 angel funds. The bulk of our VCs are private VCs. We identified 710 founders, family members, or key company employees; and 1045 corporate entities. Panel 8A also shows financing round information across the granular investor categorization. Casual angels are involved in almost half the first financing rounds, and in 65% of the companies at some stage. Serial angels and angel funds are involved in fewer companies, and especially in fewer first financing rounds. There are many more private VCs than government-supported VCs, but in the case of our data, in which the program-supported Retail VCs count as government-supported VCs, the few government-supported ones invest in more companies than the private ones. As it happens, many private out-of-province VCs make just a single investment in a BC company in our sample.

In Section 3 we pointed out that VCs make the largest funding commitments. Panel 8A shows that both private and government-supported VCs provide large amounts. In the Other Investor category, we can see that corporate investors invest larger amounts than investors in the founder and family category.

7.2 Substitutes and complements among subtypes

The theoretical framework of Section 2 is quite general. We can take any two investor subtypes and use the framework to ask whether they are substitutes or complements. To examine the relationships between all investor subtypes we simply apply the two regression models of Section 4 to the seven investor subtypes of Panel 8A. Panels 8B and 8C of Table 8 show the results for the round to round model and the early to late model, respectively. Both panels only show the new investor specification, which, as we recall, raises the bar in terms of detecting dynamic interaction effects within and across investor types when compared to the all investor specification. Find the all investor results in the Online Appendix.

Panel 8B shows the results for the round-to-round model. For most of the investor subtypes there is evidence of strong persistence within types, as revealed by the positive and statistically significant coefficients on the main diagonal. As for the dynamic interactions between the three angel subtypes (first three rows and columns) we observe a two-way substitutes relationship between casual angels and angel funds, but a complements relationship between prior casual angel funding and current serial angel funding.

This effect only goes just in one direction, i.e. there is no evidence of a relationship between prior serial angel funding and current casual angel funding. This finding is consistent with a stepping stone logic where casual angels pave the way for more experienced serial angels. Within the VC subcategories we also find an interesting asymmetry. Prior funding from private VCs is associated with a greater likelihood to encounter new government-supported VCs, but not vice versa.

Across investor types, we find a negative relationship between prior funding by casual angels and angel funding on both VC subtypes. However, the coefficients for serial angels on the VC subtypes are insignificant, suggesting that serial angels stand less apart from the VC community than casual angels or angel funds do. Looking at the reverse relationship of prior VC on current angel investing, we notice that prior government-supported VC is associated with a lower probability of both casual angels and angel funds, while there is no statistically significant effect on funding by serial angels. However, the prior presence of private VCs is associated a lower funding probability of each of the angel subcategories.

Note also some interesting patterns between angels and Other Investors. Prior funding from angel funds is negatively related to current funding from corporate investors, as well as founders & friends. This substitutes relationship applies in both directions (however note that the negative coefficient for corporate investors on angel groups is insignificant). Casual angel presence does not seem to affect or be affected by funding by corporate investors or founders, friends, and key employees, judging from the statistically insignificant coefficients. Finally, the presence of prior serial angels seems to be associated with a greater likelihood of funding by corporate investors, however this complements relationship does not flow the other way.

Panel 8C repeats the analysis of Panel 8B in the early to late model. The pattern of coefficient signs is quite similar, although the statistical significance levels tend to be lower, reflecting the lower number of observations.

Overall, the analysis of subcategories reveals several interesting insights. The most interesting result is that there are significant differences in the dynamic investment patterns of casual angels, serial angels, and angel funds. We find a fair number of complement relationships within investor types. By contrast, complements relationships between investor types are rare. This reinforces the main finding of this paper that entrepreneurial finance ecosystems may consist of parallel funding streams. In terms of exceptions, we only observe positive coefficients for the effects of prior OI-FOFA on new VC-PRIV and for the effect of prior AN-SERI on new OI-CORP.

The Online Appendix reports the results of a variety of robustness checks that are similar to those described in Subsection 4.3. It also shows the results for the performance regression of Table 6 but using the investor subtypes. Unfortunately, the BCICP data do not allow us to run an instrumental variable regression on the subcategories, as this would call for an even more fine-grained set of tax credit instruments that would apply differentially to the different subcategories.

8. Conclusion

We examine the dynamic interactions between different types of investors in innovative start-up companies. Our main focus is on the interactions between angels and VCs. Using a unique dataset from British Columbia, Canada, we find considerable support for the 'parallel streams' hypothesis that angel investors and VCs are dynamic substitutes and that this substitutes pattern is explained by a selection effect. Companies that obtain angel funding are less likely to obtain subsequent VC funding, and vice versa. The results are robust across a wide range of econometric specifications. The substitutes effect between angels and VCs is stronger for casual angels and angel funds than it is for serial angels and VCs. There are complements relationship within investor types. For example, prior funding by casual angels is associated with more funding by angel groups.

Our findings suggest that startup ecosystems may not necessarily be tightly knit networks where companies must graduate from angel funding before moving on the VC finance. Instead the evidence suggests the existence of parallel streams where different investor types cater to different types of companies, with relatively limited interactions (cross-investing) across types. These findings challenge the received wisdom that the role of angel investors is pump priming for VCs. Angels appear to cater to a different set of companies than VCs and angel-backed companies are relatively unlikely to ever switch over to VC financing. This finding is consistent with Mason et al. (2016), who argue that the increasing number of angel groups since 2000 offer an attractive option for follow-on financing for angel-backed companies.

Knowing the dynamic interaction between investor types is important for policy makers that want to foster their domestic entrepreneurial ecosystem. Currently policy makers predominantly adopt VC programs to support early-stage financing (Sandler (2004) and Wilson (2015). However, in ecosystems characterized by our parallel streams finding, angel programs would affect different types of companies than VC programs.

We see several avenues for future research. First, a natural next step would be to obtain a deeper understanding of the reasons behind the observed substitutes pattern. Is it because angels and VCs have different objective functions? Different networks? Different approaches when interacting with their companies? Or do disagreements about valuations perhaps drive the substitutes result? Second, it is important to investigate the external validity of our study. This study is based on data from British Columbia, Canada, and our empirical findings may not necessarily generalize to other ecosystems. For example, does the substitutes result also hold in large start-up ecosystems such as Silicon Valley? And does it apply to less-developed start-up ecosystems than that of British Columbia? Finally, there is an important research agenda in understanding the public policy implications. Government policies have traditionally focused on venture capital as the main path to improving the financing environment of start-ups. Yet, our main parallel streams finding challenges that approach, suggesting instead that government policies aimed at angel investors reach a different set of entrepreneurial companies that best develop or wish to develop without the involvement of venture capitalists.

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Table 1: Variable definitions

Investor categories	
Investor type	*Description*
ALL	All investors. Information on investors is collected from the BCICP data, VentureXpert, CapitalIQ, and online sources for the period between 1995 – 2009.
AN	An angel investor
AN-CASU	A casual angel investor who invests in only one company.
AN-SERI	A serial angel investor who invests in more than one company.
AN-FUND	A fund that is owned by multiple angel investors.
VC	A VC firm
VC - PRIV	A private VC firm.
VC - GOVT	A government VC firm, including all Retail VCs
OI	Other Investors.
OI – CORP	An operational corporation or financial corporation that invests
OI – FOFA	Shareholders who are either founders, family of founders, or employees of the company

Main variables.

Investment amounts measured in natural logarithms of 1 + actual investment amounts (in Can$).

Variable	Description
(a) Investor choices	
<investor type>	Dummy variable indicating the presence of at least one investor of type <investor type> in the current round.
New <investor type>	Dummy variable indicating the presence of at least one investor of type <investor type> in the current round, who did not invest in any prior round.
All <investor type>	Dummy variable indicating the presence of at least one investor of type <investor type> in the current round.
Prior <investor type>	Dummy variable indicating the presence of at least one investor of type <investor type> in any prior round.
Early <investor type>	Dummy variable indicating the presence of at least one investor of type <investor type> when company is two years of age or less.
Later <investor type>	Dummy variable indicating the presence of at least one investor of type <investor type> when company is more than two years of age.
Angel & No VC	Dummy variable indicating the presence of at least one angel investor and no VC investor.
No Angel & VC	Dummy variable indicating the presence of no angel investor and at least one VC investor.
Angel & VC	Dummy variable indicating the presence of at least one angel investor and one VC investor.
No Angel & No VC	Dummy variable indicating the presence of no angel investor or VC investor.
(b) Outcomes	

EXIT	Dummy variable that indicates if the company has exited through an IPO or successful acquisition by August 2018 (see Section 3.3 for details). The data is obtained from the SDC Global News Issue, SDC Merger, SEDAR, CapitalIQ, LexisNexis and from web searches.
FAILURE	Dummy variable that indicates if the company has failed by August 2018 (see Section 3.3 for details). The data is obtained from the BC and Canadian Company Registries, in addition to the sources used to construct the EXIT dummy above.

Control variables.

Variable	Description
(a) Company characteristics	
Industry dummies	Set of dummy variables for each of the following industries: Software, Biotech; Cleantech; IT & Telecom; Hi-tech Manufacturing; Hi-tech Services; Tourism; Other industry. Information about the companies' operation are collected from the BCICP data and from web searches for the period between 1995 and 2009.
Region dummies	Set of dummy variables for each of the following regions: Greater Vancouver (GVRD); Greater Victoria (CRD); Okanagan/Thomson Valley; and Rest of BC. Information about the companies' locations are collected from the BCICP data and from web searches for the period between 1995 and 2009.
(b) Other controls	
Cumulative Investment	Natural logarithm of one plus the cumulative investment amount (in Can$) that a company received from all previous financing rounds.
Age at First Round	Natural logarithm of the company's age measured at time of first financing plus 0.25 (in years). Information on a company's founding date is collected from the BCICP data, and from the BC and Canadian Company Registries.
Calendar Time	Quarterly non-parametric clock, i.e. dummies for each quarter of the data.
Time Since Previous Financing Round	Quarterly non-parametric clock, i.e. dummies that groups observations by time-distance since the previous round.
Time Since First Round	Quarterly non-parametric clock, i.e. dummies that groups observations by time-distance since the first round.
Share Registry Dummy	Dummy variable that takes a value of 1 if the data source of the round information is from the company share registries; and 0 if it stems from the electronic database used by the ministry.

Instrumental variables.

We use seven instruments in our IV regressions. The first set of tax credit instruments (Tax credit-RVC, tax credit-ANF, tax credit-EBC) are calculated on the basis of the 30% tax-credit supported investments amount under the RVC, ANF and EBC program segments of the BCICP. EBC Availability is an instrumental variable that indicates the availability of EBC Program during the sample period. The instruments Prior AN Supply, Prior VC Supply, and Prior OI Supply are calculated on the basis of the total (tax-credit eligible as well as non-eligible) amounts invested by Angels, Venture Capitalists and Other Investors.

All investment amounts, including tax-credit eligible investments amounts under the program, are taken from the BCICP data for the period between 1995 and 2009. All investment amounts are measured in natural logarithms of 1 + actual investment amounts (in dollars). For each company a weighted average of past aggregate tax credits is calculated, using as weights the amounts of funding actually raised by the company in a quarter, relative to the total amount raised by that company.

Variable	Description
Tax Credit – RVC	Natural logarithm of the weighted averages of past amounts of tax credits issued to companies under the RVC program.
Tax Credit – ANF	Natural logarithm of the weighted averages of past amounts of tax credits issued to companies under the angel fund program.
Tax Credit – EBC	Natural logarithm of the weighted averages of past amounts of tax credits issued to companies under the EBC program
AN Supply	Natural logarithm of the weighted averages of the total amount of angel capital market investments
VC Supply	Natural logarithm of the weighted averages of the total amount of venture capital market investments
OI Supply	Natural logarithm of the weighted averages of the total amount of investment made by other investors.

Table 2: Descriptive Statistics
Panel 2A: Descriptive Statistics at the Financing Round Level.

% of rounds involving investor types	All rounds (n=2,184)	AN Rounds (n=1,491)	VC Rounds (n=690)	OI Rounds (n=798)
AN	68.3	100	22.2	72.3
VC	31.6	10.3	100	20.4
OI	36.5	38.7	23.6	100
% of rounds involving (mutually exclusive) investor type combinations				
Angel & no VC	61.4	89.7	0.0	60.0
No Angel & VC	24.7	0.0	77.8	8.1
AN & VC	6.9	10.3	22.2	12.3
No Angel & No VC	7.0	0.0	0.0	19.6
Average round amounts ($K.)				
AN $	240	350	220	390
VC $	1,080	280	3,430	1,040
OI $	210	200	350	570
Company age (in years)				
Median age at round	3.5	3.2	4.7	3
Mean age at round	4.9	4.5	5.9	4.3
Median age at time of 1st Round	1.0	1.0	1.2	0.7
Mean age at time of 1st Round	2.4	2.3	2.7	2.2
% of follow-on rounds involving new investor types.	All rounds (n=1,715)	AN Rounds (n=1165)	VC Rounds (n=572)	OI Rounds (n=582)
No new investors	14.9	14.9	7.5	13.1
New AN	56.3	82.9	18.0	65
New VC	29.0	7.1	86.9	16.8
New OI	24.8	27.2	19.6	73.2
Average number of quarters since previous round	3.9	3.8	4.3	4.6

Table 2 (continued)
Panel 2B: Descriptive Statistics at the Company Level

Column 1: percentages and amounts applicable to the entire (observed) lifetime of the company; Column 2: percentages and amounts applicable to the first two years during the lifetime of the company; Column 3: percentages and amounts applicable to the period starting after the company turned 2 years of age. Columns 2 and 3 are based on the 447 of our 469 companies that reached an age of 2 years or older.

Variables	Companies across all rounds (n=469 companies)	Companies during Early period (n=447 companies)	Companies during Late period (n=447 companies)
% of companies with investor types			
AN	84.4	54.8	69.1
VC	37.5	18.3	33.3
OI	56.3	37.1	43.6
% of companies with (mutually exclusive) investor type combinations			
Angel & No VC	61.6	46.3	52.3
No Angel & VC	14.7	9.8	16.6
Angel & VC	22.8	8.5	16.8
No Angel & No VC	0.9	3.4	0.9
No round in period	N/A	32.0	13.4
Amounts ($K.)			
AN $	1,118	401	749
VC $	5,040	847	4,420
OI $	971	311	708
Industry (% of companies)		N/A	N/A
Software	28.1		
Biotech	12.2		
Cleantech	5.3		
IT & Communication	7.0		
Hi-tech Manufacturing	17.9		
Hi-tech Service	6.0		
Tourism	7.7		
Other	15.8		
Location (% of companies)		N/A	N/A
GVRD (Vancouver)	72.9		
CRD (Victoria)	7.5		
Okanagan & Thompson River	5.1		
Rest of BC	14.5		

Table 2 (continued)
Panel 2C: Investor Types and How Much Funding they Collectively Provide

Column 1: number and percentage of companies that received funding in the first round from one or more investors of the row type. Column 2: the per-company average funding amount provided in the first round by investors of the row type, conditional on there being at least one such an investor. Column 3: the numbers and percentages of companies that received funding in any round from one or more investors of the row type. Column 4: the per-company average funding amount provided across all rounds by investors of the row type, conditional on there being at least one such an investor.

Investor type(s)	Number of distinct investors	First Round Investments		All Rounds Investments	
		1	2	3	4
		# Companies Funded (%)	Avg. Funding Amount if Amount >0 (in $K.)	# Companies Funded (%)	Avg. Funding Amount if Amount >0 (in $K.)
All	9,424	469 (100%)	1,160	469 (100%)	7,130
AN	7,215	328 (70%)	440	394 (84%)	1,320
VC	454	117 (25%)	2,300	178 (38%)	13,430
OI	1,755	215 (46%)	590	262 (56%)	1,730

Table 2 (continued)
Panel 2D: Investor Transition Probabilities: First Round to Ever

Frequencies of transitions between the first round and all financing rounds of our companies. We map investor compositions into four mutually exclusive states. For the first round the "Angel & no VC" state means that in this first round there was at least one angel, while there was no VC (possibly there were Other Investors too). For the "Ever" dimension "Angel & no VC" means that across all rounds there was at least one angel, but no VC (possibly there were Other Investors too). "No Angel & VC", "Angel & VC", and "No Angel & No VC" are defined in an analogous way. For example, the 84.7% figure below shows that of the companies that had at least one angel, but no VC in the first round, 84.7 remained in the situation of having just angel investors, but no VC during all other rounds as well.

		Ever (During the Company's Life)			
		Angel & No VC	No Angel & VC	Angel & VC	No Angel & No VC
First Round	Angel & no VC	84.7%	0.0%	15.3%	0.0%
	No Angel & VC	0.0%	80.2%	19.8%	0.0%
	Angel & VC	0.0%	0.0%	100.0%	0.0%
	No Angel & no VC	70.2%	0.0%	22.8%	7.0%

Panel 2E: Investor Transition Probabilities: Round to Round

Frequencies of transitions between the previous and the current financing rounds of our companies. We map investor-type compositions in each round into four mutually exclusive categories. In each round "Angel & no VC" means that there was at least one angel but no VC in that particular round (possibly there were Other Investors too). "No Angel & VC", "Angel & VC", and "No Angel & No VC" are defined in an analogous way.

		Current Round			
		Angel & No VC	No Angel & VC	Angel & VC	No Angel & No VC
Previous Round	Angel & No VC	87.5%	3.3%	4.4%	4.8%
	No Angel & VC	3.4%	91.7%	4.1%	0.7%
	Angel & VC	29.1%	27.6%	38.8%	4.5%
	No Angel & No VC	63.2%	2.3%	4.5%	30.1%

Table 2 (continued)
Panel 2F: Investor Transition Probabilities: Early period to late period

Frequencies of transitions between investor-compositions during the early period and the late period of our companies. Here the early period is defined as the first two years of the company's life, and the late period all years that follow. We map investor-type compositions into four mutually exclusive categories. For each period "Angel & no VC" means that at least one angel invested in that period, while no VC invested (possibly Other Investors invested too in the period). "No Angel & VC", "Angel & VC", and "No Angel & No VC" are defined in an analogous way.

		Late period			
		Angel & No VC	No Angel & VC	Angel & VC	No Angel & No VC
Early Period	Angel & No VC	62.3%	3.4%	11.6%	22.7%
	No Angel & VC	4.5%	72.7%	11.4%	11.4%
	Angel & VC	15.8%	21.1%	39.4%	23.7%
	No Angel & No VC	61.4%	17.1%	19.6%	1.9%

Panel 2G: Investor Transition Probabilities: Early period to late period for new investors

Frequencies of transitions between investor-compositions during the early period and the late period of our companies. Here the early period is defined as the first two years of the company's life, and the late period all years that follow. We map investor-type compositions into four mutually exclusive categories. For each period "New Angel & No New VC" means that at least one new angel invested in that period, while no new VC invested (possibly Other Investors invested too in the period). "No New Angel & New VC", "New Angel & New VC", and "No New Angel & No New VC" are defined in an analogous way.

		Late period			
		New Angel & No New VC	No New Angel & New VC	New Angel & New VC	No New Angel & No New VC
Early Period	Angel & No VC	54.6%	3.3%	11.7%	30.4%
	No Angel & VC	4.5%	72.7%	11.4%	11.4%
	Angel & VC	15.8%	18.4%	34.2%	31.6%
	No Angel & No VC	61.4%	17.1%	19.6%	1.9%

Table 2 (continued)
Panel 2H: Company Performance and Investor composition

Relationship between the investor types the company has attracted during the time that we observe the company and company performance as measured by its exit status. IPO, Acquired, Failure and Active reflect are company's possible exit statuses, as observed on August 2018, i.e. over 8 years after the latest round for all companies. All investor type states reflect the investors the company attracted across all observed rounds, i.e., according to the "ever" dimension in Panel D. For example, the cell saying "6 (2.1%)" shows that among the 289 companies that received funding from one or more angels, but not from a VC across all rounds, there were 6 companies (or 2.1%) that had an IPO.

Company Performance		Investor composition at the end of the sample period				
		Angel & No VC	No Angel & VC	Angel & VC	No Angel & No VC	Total
	IPO	6 (2.1%)	5 (7.3%)	13 (12.2%)	0 (0%)	24 (5.1%)
	Acquired	29 (10.0%)	32 (46.4%)	24 (22.4%)	0 (0%)	85 (18.1%)
	Failure	160 (55.4%)	29 (42.0%)	44 (41.1%)	2 (50%)	235 (50.1%)
	Active	94 (32.5%)	3 (4.3%)	26 (24.3%)	2 (50%)	125 (26.7%)
	Total	289 (61.6%)	69 (14.7%)	107 (22.8%)	4 (0.9%)	469 (100%)

Table 2 (continued)
Panel 2I: Correlation matrix of key company variables

Correlations between several key variables at the company level, namely dummy variables of Angels, VCs, and Other Investors in the first round; dummies of the accumulation of these investor types over all rounds; and dummies indicating the exit and survival of the companies at the time we last collected survival data in August 2018. P-values are in parentheses.

Time	Variables	At First Round			At the End of Sample			Outcomes	
		AN	VC	OI	AN	VC	OI	Exit	Failure
At First Round	AN	1							
	VC	-0.5339	1						
		(0.000)							
	OI	-0.0013	-0.2104	1					
		(0.977)	(0.000)						
At the End of Sample	AN	0.6483	-0.6863	0.2551	1				
		(0.000)	(0.000)	(0.000)					
	VC	-0.4337	0.7481	-0.1154	-0.5054	1			
		(0.000)	(0.000)	(0.012)	(0.000)				
	OI	-0.0421	-0.1231	0.8142	0.1789	0.0450	1		
		(0.363)	(0.007)	(0.000)	(0.000)	(0.331)			
Outcomes	Exit	-0.2606	0.3324	-0. 1033	-0.2790	0.3451	0.0167	1	
		(0.000)	(0.000)	(0.025)	(0.000)	(0.000)	(0.7178)		
	Failure	0.0894	-0.0897	-0.0533	0.0656	-0.1338	-0.0884	-0.5514	1
		(0.053)	(0.052)	(0.249)	(0.156)	(0.004)	(0.056)	(0.000)	

Table 3: The Relationship between Prior and Current Investors – Round to Round Model

Results of panel OLS regressions at the financing round level. The dependent variables are dummy variables indicating the presence of new investors of a certain type (Columns 1-3) and any investors of a certain type (Columns 4-6) in the current financing round. The main independent variables are dummy variables indicating whether a company received funding from each investor type prior to the current financing round. The other reported independent variables are company age at the first investment round, cumulative financing amount received up to the current financing round, region dummies, and industry dummies. The omitted categories for region dummies and industry dummies are Greater Vancouver and Software respectively. The unreported control variables are the share registry dummy, three (quarterly) non-parametric clocks for calendar time, time passed since the previous financing round, and time passed since the first round. A constant was also included but not shown. All variables are defined in Table 1. Robust standard errors, clustered at the company level, are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) New AN	(2) New VC	(3) New OI	(4) All AN	(5) All VC	(6) All OI
Prior AN	0.300***	-0.347***	-0.0788**	0.419***	-0.226***	-0.0482
	(0.0392)	(0.0360)	(0.0332)	(0.0390)	(0.0337)	(0.0332)
Prior VC	-0.246***	0.300***	-0.00208	-0.275***	0.492***	-0.0262
	(0.0489)	(0.0419)	(0.0331)	(0.0431)	(0.0457)	(0.0338)
Prior OI	-0.0309	-0.0916***	0.153***	-0.00661	-0.0485**	0.245***
	(0.0385)	(0.0224)	(0.0322)	(0.0274)	(0.0200)	(0.0356)
Age at First Round	-0.00170	0.00435*	-0.00223	-0.00301	0.00296	-0.00251
	(0.00366)	(0.00247)	(0.00331)	(0.00278)	(0.00227)	(0.00260)
Cumulative Past Investment	-0.0347***	0.0235***	-0.00154	-0.0187***	0.0209***	-0.00329
	(0.00730)	(0.00472)	(0.00625)	(0.00552)	(0.00488)	(0.00613)
Capital Region District	0.0384	0.0359	-0.0295	0.0319	0.0289	-0.0253
	(0.0531)	(0.0273)	(0.0322)	(0.0341)	(0.0274)	(0.0385)
Okanagan Thomson	-0.0507	-0.0144	0.00543	0.0281	-0.0433	0.0142
	(0.0646)	(0.0291)	(0.0607)	(0.0404)	(0.0290)	(0.0656)
Rest of BC	0.0618	-0.0489**	-0.00409	0.0728***	-0.0602***	-0.0397
	(0.0427)	(0.0223)	(0.0392)	(0.0242)	(0.0205)	(0.0431)
Biotech	0.0369	0.0134	0.0533	0.0183	0.0172	-0.00900
	(0.0414)	(0.0315)	(0.0372)	(0.0366)	(0.0335)	(0.0393)
Cleantech	0.152***	0.00196	-0.0234	0.108***	0.0370	-0.131**
	(0.0536)	(0.0393)	(0.0530)	(0.0354)	(0.0466)	(0.0614)
IT & Telecom	0.00642	0.0776*	0.0106	-0.00450	0.0678	-0.0118
	(0.0721)	(0.0450)	(0.0492)	(0.0537)	(0.0440)	(0.0532)
High-tech Manufacturing	0.0332	-0.00644	0.0142	0.0369	-0.00498	0.0268
	(0.0458)	(0.0300)	(0.0357)	(0.0323)	(0.0273)	(0.0382)
High-tech Services	-0.0794	-0.105***	-0.0512	0.0337	-0.0635*	-0.0682
	(0.0646)	(0.0356)	(0.0668)	(0.0370)	(0.0368)	(0.0751)
Tourism	-0.0242	-0.111***	-0.114*	0.0417	-0.0958***	-0.105
	(0.0676)	(0.0282)	(0.0613)	(0.0520)	(0.0257)	(0.0653)
Other Industry	0.0657	-0.0634**	-0.0444	0.0391	-0.0479**	-0.0906**
	(0.0477)	(0.0279)	(0.0370)	(0.0357)	(0.0235)	(0.0416)
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.385	0.648	0.284	0.586	0.706	0.398
Observations	1,715	1,715	1,715	1,715	1,715	1,715
Number of companies	469	469	469	469	469	469

Table 4: The Relationship between Prior and Current Investors – Early to Late Model

Results of cross section OLS regressions at the company level. The dependent variables are dummy variables indicating the "arrival" of new (Columns 1-3) and all (Columns 4-6) investors of a certain type in the late period of the company's life (when it was older than 2 years of age). The main independent variables are dummy variables indicating whether a company received funding from the investor type in the early period (before it turned 2 years of age). The unreported independent variables are company age at the first investment round, the cumulative financing amount received in the company's early period, region dummies, industry dummies, and the share registry dummy. A constant was also included but not shown. All variables are defined in Table 1. Robust standard errors, clustered at the company level, are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	New Late AN	New Late VC	New Late OI	All Late AN	All Late VC	All Late OI
Early AN	-0.0839	-0.185***	-0.325***	0.00370	-0.169***	-0.349***
	(0.0547)	(0.0499)	(0.0572)	(0.0532)	(0.0497)	(0.0557)
Early VC	-0.378***	0.352***	-0.246***	-0.380***	0.397***	-0.280***
	(0.0667)	(0.0639)	(0.0694)	(0.0640)	(0.0630)	(0.0689)
Early OI	0.179***	0.00915	0.383***	0.156***	0.0265	0.431***
	(0.0554)	(0.0444)	(0.0508)	(0.0531)	(0.0441)	(0.0500)
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.169	0.292	0.193	0.177	0.307	0.225
Observations	447	447	447	447	447	447
Number of Companies	447	447	447	447	447	447

Table 5. The Relationship between Prior and Current Investors – Instrumental Variables Regression

First-stage regressions

Results from the first and second stage of an instrumental variable regression at the financing round level. The dependent variables of the second-stage regression are dummy variables indicating the presence of new investors (Columns 1-3) and all investors (Columns 4-6) of a certain investor type in the current financing round. The main independent variables are IVs generated from the first stage regressions. The instruments "Tax credits – <BCICP program-segment>" are the natural logs of the weighted averages of past amounts of tax credits issued to companies under the RVC, ANF and EBC program-segments in the quarter when the financing round happened. The weighted averages are taken over companies' entire investment histories, where the weights are the relative amounts raised by the company across different rounds. The EBC Availability is defined as the average number of quarters during which the EBC program was available, for the period from the company's first investment to the last quarter prior to the current round. The variables "Prior <Investor type> Supply" are defined as the natural logarithm of the weighted averages of the total amount of market investments in the quarter when the financing round happened, broken down by investor type (AN, VC, and OI). The weights are the same as for the tax credits measures. The unreported control variables are company age at the first investment round, the cumulative financing amount received up to the current financing round, region dummies, industry dummies, the share registry dummy, three (quarterly) non-parametric clocks for calendar time, time passed since the previous financing round, and time passed since the first round. A constant was also included in the regression. Standard errors are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Prior AN	(2) Prior VC	(3) Prior OI
Tax credits – RVC	-0.0011	0.0024**	-0.0033***
	(0.0011)	(0.0011)	(0.0011)
Tax credits – ANF	0.0055	-0.0176**	0.0194***
	(0.0065)	(0.0069)	(0.0066)
Tax credits – EBC	0.004***	-0.0019	-0.0003
	(0.0013)	(0.0013)	(0.0013)
EBC Availability	0.5786**	-0.3683	0.7925***
	(0.2773)	(0.2947)	(0.282)
Prior AN Supply	0.0028	0.0384	0.012
	(0.0251)	(0.0267)	(0.0255)
Prior VC Supply	0.0135	-0.0105	0.0306**
	(0.01256)	(0.0133)	(0.0128)
Prior OI Supply	-0.0051	0.0039	-0.0023
	(0.0039)	(0.0041)	(0.004)
Constant & Controls	YES	YES	YES
R-squared	0.0634	0.388	0.3502
Observations	1,663	1,663	1,663
Number of companies	465	465	465
Joint-significance test of the instruments (first stage)			
Chi-square (7)	16.83	13.35	27.32
p-value	0.0185	0.0641	0.0030

Second-stage regressions

VARIABLES	(1) New AN	(2) New VC	(3) New OI	(4) All AN	(5) All VC	(6) All OI
Prior AN - IV Augmented	0.437	0.233	0.728	0.269	-0.173	0.826
	(0.589)	(0.472)	(0.465)	(0.401)	(0.431)	(0.509)
Prior VC - IV Augmented	0.295	0.650	0.784	0.280	0.711	0.430
	(0.722)	(0.528)	(0.497)	(0.529)	(0.485)	(0.687)
Prior OI - IV Augmented	-0.132	-0.109	0.475	0.221	0.0908	0.187
	(0.512)	(0.356)	(0.620)	(0.535)	(0.328)	(0.660)
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.1931	0.4016	0.1144	0.2550	0.6730	0.1804
Observations	1,663	1,663	1,663	1,663	1,663	1,663
Number of companies	465	465	465	465	465	465

Table 6: Investor Choices and Company Performance

Columns 1 and 2: Results from two panel OLS regressions at the 'augmented financing round level' (see Section 6.2 for details) Columns 3 and 4: Results from two cross section OLS regressions at the company level. The dependent variables in the regressions are dummy exit outcome variables indicating whether a company has exited or failed (multiplied by 100 for a better presentation of the result). The main independent variables in the two panel OLS regressions are dummy variables indicating whether a company received funding from an investor type in the previous round. The main independent variables in the two cross section OLS regressions are dummy variables indicating whether a company received funding from an investor type at any moment prior to the company's exit moment, if any. The unreported control variables are company age at the first investment round, region dummies, industry dummies, and the share registry dummy. A constant was also included but not shown. All variables are defined in Table 1. Robust standard errors, clustered at the company level, are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Exit x 100	Failure x 100	Exit x 100	Failure x 100
Prior AN	-2.284	3.067*		
	(1.474)	(1.679)		
Prior VC	2.400	-2.294		
	(1.467)	(1.923)		
Prior OI	1.292	1.542		
	(1.390)	(1.730)		
Stock AN			-13.01	7.962
			(8.739)	(9.766)
Stock VC			14.82**	-9.836
			(7.387)	(9.118)
Stock OT			3.355	2.559
			(5.618)	(6.401)
Controls	YES	YES	YES	YES
R-squared	0.267	0.279	0.576	0.580
Observations	2,168	2,168	469	469
Number of companies	469	469	469	469
	Prior AN = Prior VC		Stock AN = Stock VC	
Chi Square (1)	10.73	8.60		
F (1, 468)			8.33	3.03
P-value	0.0011	0.0034	0.0041	0.0826

Table 7: The Relationship between Prior and Current Investors – Subsamples of Exited and Failed Companies

Panel 7A: Round to Round Model

Results of panel OLS regressions at the financing round level. The dependent variables are dummy variables indicating the presence of new investors of a certain type in the current financing round. The main independent variables are dummy variables indicating whether a company received funding from each investor type prior to the current financing round. Columns 1-3 show results in the subsample of companies that had an exit. Columns 4-6 show results in the subsample of failed companies. The unreported control variables are company age at the first investment round, cumulative financing amount received up to the current financing round, region dummies, industry dummies, the share registry dummy, three (quarterly) non-parametric clocks for calendar time, time passed since the previous financing round, and time passed since the first round. A constant was included but not shown. All variables are defined in Table 1. Robust standard errors, clustered at the company level, are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EXITED COMPANIES			FAILED COMPANIES		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	New AN	New VC	New OI	New AN	New VC	New OI
Prior AN	0.302***	-0.321***	-0.0964	0.285***	-0.334***	-0.104**
	(0.0676)	(0.0735)	(0.0612)	(0.0620)	(0.0519)	(0.0518)
Prior VC	-0.324***	0.380***	-0.0275	-0.251***	0.296***	-0.0139
	(0.0802)	(0.0764)	(0.0744)	(0.0781)	(0.0602)	(0.0517)
Prior OI	-0.0532	-0.0887*	0.137**	-0.0457	-0.110***	0.145***
	(0.0607)	(0.0466)	(0.0618)	(0.0634)	(0.0330)	(0.0463)
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.691	0.717	0.510	0.409	0.685	0.369
Observations	461	461	461	742	742	742
Number of companies	109	109	109	235	235	235

Table 7 (continued)

Panel 7B: Early to Late Model

Results of cross section OLS regressions at the company level. The dependent variables are dummy variables indicating the "arrival" of new investors of a certain type in the late period of the company's life (when the company was older than two years of age). The main independent variables are dummy variables indicating whether a company received funding from each investor type during the early period of the company's life (when the company was up to and including two years of age). Columns 1-3 show the results in the subsample of companies that had an exit. Columns 4-6 show the results in the subsample of companies that had failed by August 2018. The unreported control variables are company age at the first investment round, the cumulative financing amount received during the company's first two years of age, region dummies, industry dummies, and the share registry dummy. A constant was included but not shown. All variables are defined in Table 1. Robust standard errors, clustered at the company level, are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	EXITED COMPANIES			FAILED COMPANIES		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	New Late AN	New Late VC	New Late OI	New Late AN	New Late VC	New Late OI
Early AN	0.233*	-0.430***	-0.0998	-0.177**	-0.183***	-0.511***
	(0.127)	(0.113)	(0.129)	(0.0795)	(0.0686)	(0.0759)
Early VC	-0.271**	0.159	-0.105	-0.436***	0.283***	-0.443***
	(0.128)	(0.127)	(0.135)	(0.107)	(0.0971)	(0.104)
Early OI	0.187	0.0794	0.416***	0.102	0.0264	0.351***
	(0.113)	(0.103)	(0.124)	(0.0811)	(0.0586)	(0.0690)
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.270	0.321	0.204	0.201	0.311	0.290
Observations	107	107	107	215	215	215
Number of companies	107	107	107	215	215	215

Table 8: The Relationship between Prior and Current Investors – Regressions with Investor Subtypes
Panel 8A: Company funding by investor subtypes

The three non-numbered columns show the investor type sub-categories, the number of investors of each investor sub-type, and the percentage of rounds which involved an investment by at least one investor of the row sub-type. Numbered Column 1: number and percentage of companies that received funding in the first round from one or more investors of the row subtype. Column 2: the per-company average funding amount provided in the first round by the investor of the row subtype, conditional on the presence of such an investor. Column 3: the numbers and percentages of companies that received funding in any round from one or more investors of the row subtype. Column 4: the per-company average funding amount provided across all rounds by the investor of the row subtype, conditional on the presence of such an investor. The investor subtypes are defined in Table 1.

Investor type(s)	Number of distinct investors	Percentage of rounds involved	First Round Investments		All Rounds Investments	
			1	2	3	4
			# Companies Funded (%)	Avg. Funding Amount if Amount>0 (in $K)	# Companies Funded (%)	Avg. Funding Amount if Amount>0 (in $K)
AN - CASU	6801	47	230 (49%)	480	305 (65%)	1,050
AN - SERI	214	16	79 (17%)	30	164 (35%)	170
AN - FUND	200	28	140 (30%)	390	220 (47%)	950
VC - PRIV	443	15	56 (12%)	1,880	126 (27%)	10,410
VC - GOVT	11	26	89 (19%)	1,850	150 (32%)	7,080
OI - CORP	710	23	122 (26%)	540	206 (44%)	1,520
OI - FOFA	1045	26	164 (35%)	380	192 (41%)	620

Table 8 (continued)

Panel 8B: Round to Round Model with Investor Subtypes.

Results of panel OLS regressions at the financing round level. The dependent variables are dummy variables indicating the presence of new investors of a certain subtype in the current financing round. The main independent variables are dummy variables indicating whether a company received funding from each investor subtype prior to the current financing round. The unreported control variables are company age at the first investment round, cumulative financing amount received up to the current financing round, region dummies, industry dummies, the share registry dummy, three (quarterly) non-parametric clocks for calendar time, time passed since the previous financing round, and time passed since the first round. A constant was included but not shown. All variables are defined in Table 1. Robust standard errors, clustered at the company level, are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) New AN - CASU	(2) New AN - SERI	(3) New AN - FUND	(4) New VC - PRIV	(5) New VC - GOVT	(6) New OI - CORP	(7) New OI – FOFA
Prior AN – CASU	0.310***	0.0917***	-0.0654**	-0.0838***	-0.167***	-0.0266	-0.0223
	(0.0406)	(0.0285)	(0.0324)	(0.0214)	(0.0270)	(0.0281)	(0.0242)
Prior AN – SERI	0.00994	0.0687**	-0.0179	0.00258	-0.00858	0.0536**	0.0224
	(0.0383)	(0.0327)	(0.0329)	(0.0169)	(0.0241)	(0.0262)	(0.0271)
Prior AN – FUND	-0.186***	-0.0124	0.120***	-0.0856***	-0.143***	-0.0660***	-0.0541***
	(0.0300)	(0.0218)	(0.0329)	(0.0179)	(0.0244)	(0.0231)	(0.0194)
Prior VC – PRIV	-0.0561*	-0.0512*	-0.104***	0.208***	0.0637*	0.0253	-0.0102
	(0.0335)	(0.0293)	(0.0363)	(0.0376)	(0.0376)	(0.0343)	(0.0216)
Prior VC – GOVT	-0.167***	0.0239	-0.127***	0.0234	0.347***	0.0196	0.00860
	(0.0347)	(0.0291)	(0.0377)	(0.0331)	(0.0412)	(0.0309)	(0.0246)
Prior OI – CORP	-0.0505	-0.0287	-0.0509*	-0.0252	-0.0691***	0.00895	0.0849***
	(0.0447)	(0.0306)	(0.0298)	(0.0161)	(0.0251)	(0.0319)	(0.0267)
Prior OI – FOFA	0.0275	-0.0103	-0.00346	0.0549***	-0.0449**	0.134***	0.0140
	(0.0333)	(0.0229)	(0.0266)	(0.0188)	(0.0206)	(0.0281)	(0.0248)
Controls	YES	YES	YES	YES	YES	YES	YES
R-squared	0.434	0.1561	0.2696	0.3861	0.5822	0.1857	0.3159
Observations	1,715	1,715	1,715	1,715	1,715	1,715	1,715
Number of companies	469	469	469	469	469	469	469

Table 8 (continued)

Panel 8C: Early to Late Model with Investor Subtypes

Results of cross section OLS regressions at the company level. The dependent variables are dummy variables indicating the "arrival" of new investors of a certain subtype during the late period of the company's life (when the company was older than two years of age). The main independent variables are dummy variables indicating whether a company received funding from a certain subtype during the early period of its life (when the company up to and including 2 years of age). The unreported independent variables are company age at the first investment round, cumulative financing amount received in a company's first two years of age, region dummies, industry dummies, and the share registry dummy. A constant was also included but not shown. All variables are defined in Table 1. Robust standard errors, clustered at the company level, are reported in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

VARIABLES	(1) New Late AN - CASU	(2) New Late AN - SERI	(3) New Late AN - FUND	(4) New Late VC - PRIV	(5) New Late VC - GOVT	(6) New Late OI - CORP	(7) New Late OI – FOFA
Early AN – CASU	0.0178	-0.0877	-0.257***	-0.141***	-0.137***	-0.250***	-0.147**
	(0.0665)	(0.0585)	(0.0586)	(0.0505)	(0.0452)	(0.0605)	(0.0570)
Early AN – SERI	-0.0402	0.105	-0.0446	0.0315	-0.0618	-0.00269	-0.0385
	(0.0705)	(0.0645)	(0.0582)	(0.0541)	(0.0481)	(0.0676)	(0.0593)
Early AN – FUND	-0.241***	-0.0950**	0.182***	-0.138***	-0.101**	-0.169***	-0.158***
	(0.0495)	(0.0428)	(0.0513)	(0.0394)	(0.0432)	(0.0483)	(0.0391)
Early VC – PRIV	-0.0364	-0.0528	-0.0153	0.184**	0.118	-0.0260	-0.0557
	(0.0806)	(0.0732)	(0.0748)	(0.0841)	(0.0827)	(0.0914)	(0.0667)
Early VC – GOVT	-0.323***	-0.171**	-0.322***	0.155**	0.355***	-0.222***	-0.254***
	(0.0703)	(0.0664)	(0.0681)	(0.0778)	(0.0799)	(0.0747)	(0.0547)
Early OI – CORP	0.136**	0.0143	-0.0557	0.108**	0.0184	0.185***	0.103*
	(0.0638)	(0.0590)	(0.0542)	(0.0483)	(0.0470)	(0.0667)	(0.0598)
Early OI – FOFA	0.274***	0.209***	0.179***	0.0247	0.00628	0.285***	0.342***
	(0.0654)	(0.0580)	(0.0522)	(0.0486)	(0.0443)	(0.0614)	(0.0579)
Controls	YES	YES	YES	YES	YES	YES	YES
R-squared	0.236	0.104	0.153	0.230	0.305	0.154	0.218
Observations	447	447	447	447	447	447	447
Number of companies	447	447	447	447	447	447	447