With a Little Help from My Friends:
Access to External Resources and Venture Capital Stage Drift

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ABSTRACT

This research takes a novel approach to the concept of venture capital stage drift by assessing the influence of having access to other VC funds' resources. A comprehensive U.S. dataset containing investments from 1980 until 2010 is constructed. Robust evidence is found that VC funds with increased access to other funds' resources are more likely to downward drift, whereas some evidence is found that these funds are less likely to upward drift. Furthermore, when more money flows into the VC industry, funds with better past performance are less keen to perform stage drifts toward less risky stages, relative to funds with poor past performance. In contrast, when less money flows into the industry, the inverse is true. This is consistent with agency theory explanations of termination risk and fund inflow incentives.

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1. INTRODUCTION

Venture capital (VC) financing is a form of private equity financing that is given to early stage, expansion stage and later stage companies that frequently have too little operating history or whose profile is too risky to obtain other forms of capital. A VC firm has one or more VC funds, which invest in companies in exchange for equity. When a VC fund includes a company in its portfolio whose characteristics are not fully aligned with the fund's stated objectives the fund 'style drifts'. In general style drift carries a negative connotation for limited partners (LPs). Coller Capital, a leading investor in private equity, states in their '2012 - 2013 Global Private Equity Barometer' survey that style drift is one of greatest concerns for LPs, with 73% of fund LPs viewing it negatively (Coller Capital, 2012). LPs often frown on style drift, as it results in a deviation from their own risk-return allocation strategy (Buzzacchi et al., 2015). Given the long-term nature of VC investments, LPs do not have the immediate possibility to withdraw their capital when style drift occurs if they view it as negative for their portfolio composition. However, style drift seems to be performed frequently in private equity, and Cumming et al. (2009) find that 56% of all VC fund investments are style drifts.

There is a considerable gap in our knowledge regarding style drift in venture capital. Previous work on style drift has mainly concerned mutual funds and focused on agency costs and risk shifting, finding evidence that 'termination risk', the risk of a fund manager losing his job due to bad performance, and 'fund inflow incentives', wherein better performing managers receive more funding from LPs, can both lead to risk shifting. In particular, studies consistently find that fund managers that underperform in the first half of the year shift to higher risk strategies due to termination risk (Brown et al., 1996; Qiu, 2003; Schwarz, 2013). Better performing funds are found to lock in their profits by shifting to reduce risk (Brown et al., 1996), while top performing funds increase risk because of fund inflow incentives (Qiu, 2003; Hu et al., 2011). Different market conditions are also found to change incentives, with termination risk dominating for losers in bear markets, when the probability of job loss is the highest, and fund inflow incentives being crucial for winners in bull markets, when the largest amount of funds are available (Kempf and Ruenzi, 2008).

In private equity research, the only papers on style drift I am aware of are those of Cumming et al. (2009) and Buzzacchi et al. (2015), who examine style drifts by examining style drift in terms of the entrepreneurial company's development stages (henceforth stage drift). Both pieces of research focus on agency costs and the effect of market conditions. Cumming et al. (2009) look at the reputation costs of stage drifting in private equity and display that younger managers have a higher cost of drifting and that they stage drift less. In addition, they also find evidence that when market opportunities are good, later stage VC funds drift more while earlier stage VC funds drift less. Buzzacchi et al. (2015) examine venture capital stage drift and define stage drift into higher stages as ‘upward drift’ (henceforth upward drift), where VC funds shift into more risk, and stage drift into lower stages as ‘downward drift’ (henceforth downward drift), where VC funds shift into less risk. They show that a higher hurdle rate discourages managers from lowering risk, and that more reputable fund managers take less risk. In addition, they find evidence consistent with that of mutual fund research, as fund managers with poor past performance are less likely to ‘play it safe’ by upward drifting, an effect that grows stronger in bull markets.

My research differs from previous literature in two main aspects. First, I hypothesize that the resources of partner VC firm (VCF) can induce a VC fund to stage drift. A key competitive advantage for VCFs is their network, in the entrepreneur-VCF spectrum as well as between VCFs themselves (Hochberg et al., 2007). A network among VCFs has been defined as ‘access to external resources’, with access to other VCF’s ‘selection resources’ increasing the ability to screen for better investments (Bygrave, 1987; Sorenson and Stuart, 2001) and ‘treatment resources’ enhancing the VCF’s ability to add value to the portfolio companies (Hochberg et al., 2015). It is thus highly likely that if opportunities due to differing market conditions can lead to stage drift, external resource access can also lead to such opportunities. I expect VC funds with more access to such resources via their VCF parent to be able to make use of this competitive advantage by both downward drifting and upward drifting more.

Second, to my knowledge this research is the first to look at stage drift for VC funds in a U.S. setting. U.S. and European VC funds have been found to be structurally different (Schwienbacher, 2005). The work of Buzzacchi et al. (2015) is expanded upon using a much larger sample, and a new methodology is taken to exclude future performance when mapping out agency costs by examining past performance. A perspective into the changeability of the behavior of poor and better past performing funds is taken by analyzing fund inflows instead of market conditions. Finally, it is shown that market conditions still have a significant effect on downward drift after controlling for fund inflows.

In my analysis, I use a database of 12,968 investments by 2,195 U.S.-based VC funds from 1980 until 2010 that commit to a certain style. I firstly present that VC funds with a higher access to external resources downward drift more, which is consistent with expectations. However, for upward drift some evidence is found that VC funds with a higher access to resources upward drift less, and four possible reasons for this are presented. In addition, evidence of agency theory is found, as when less money flows into the VC industry better performing funds tend to be less keen on ‘playing it safe’ by stage drifting toward less risky stages in comparison to poorly performing funds. However, when fund inflows are low, the effects reverse and poorly performing funds are less keen on playing it safe in comparison with better performing funds. These effects are consistent with termination risk and fund inflow incentives, respectively. Finally, better market opportunities have been found to increase the amount of risk a fund takes.

The remainder of this paper is structured as follows. Section 2 discusses the literature, the perspective this paper takes on resources, as well as the role of resource access and stage drift. Section 3 develops the research question and the hypotheses used. Section 4 documents the sources of data, and the construction of the variables used in the analysis and the models. Section 5 presents the findings. Section 6 concludes by summarizing the research and pointing out areas for further research.

2. LITERATURE REVIEW

The literature review begins with an outline of the paradigm this paper takes, namely the resource-based view, and shows the resources which are available to a VCF. Afterwards, the literature on the network and syndication is examined, which fits the network as a way to these access resources in the resource-based view. Finally, the literature on drifting is discussed, and the reasons and circumstances that might cause a VC fund to stage drift, leading up to the question if this could be done due to external resources.

2.1 VCF Resources

The resource-based view (RBV) explains a VCF's competitive advantage. It focuses on a VCF's resources and capabilities, with the underlying premise that for a VCF to achieve a competitive advantage it must control and acquire valuable and/or rare capabilities and resources. However, to be able to sustain this competitive advantage, the resources and capabilities must have the characteristics of inimitability, non-substitutability, and non-transferability. Finally, these resources and capabilities alone are insufficient, as a VCF also needs to have the organization in place to be able to implement the capabilities (Wernerfelt, 1984; Peteraf, 1993; Barney, 2001). In general, the resources of a VCF can be categorized as either selection or treatment resources. Selection resources are exploited before the investment is made, providing the opportunity to make better investment choices, while treatment resources add value to a portfolio company after the investment is made, by monitoring and aiding in operations, if necessary (Castanias and Helfat, 1991; Hochberg et al., 2015). There are multiple ways of establishing a competitive advantage using both resources. However, in practice it is often hard to differentiate between them (Sørensen, 2007), as for instance a specialization in a certain industry can lead to both better an increased skill in investment selection, as well an increased ability to add value.

A competitive advantage for a VCF can be built by specialization, in terms of entrepreneurial stage of development, industry or geography. Norton and Tenenbaum (1993) find that instead of diversifying into a range of investment stages, VCFs typically aim to control portfolio risk by actively specializing in a certain stage, consequently building up a reputation to become central members in a VC network. Later work by Gompers et al. (2009) finds that greater levels of industry specialization of fund managers can lead to a higher chance of successful investments. Finally, Sorensen and Stuart (2001) state that VCFs tend to specialize in an industry or geographic area due to the ability to receive higher quality information as a result of the narrower focus.

Another key resource that may provide a competitive advantage is the VCF's reputation. Nahata (2008) finds that VCFs with a better reputation have more successful exits, and that reputation is a proxy for both the selection and treatment resources. As demonstrated by the work of Hsu (2004), entrepreneurs are willing to accept worse valuations for their companies from VCFs with a better reputation, which shows indirect evidence of treatment effects.

Moreover, a resource for VCFs is having strong connections outside of the VCF-entrepreneur spectrum, such as access to industry specialists or other reputable institutions. A considerable amount of prior research has examined the role of auditors and banks in the IPO process (Carter and Singh, 1998; Gulati and Higgins, 2003), finding that the use of higher quality banks as underwriters can have a certification effect, resulting in a higher price at IPO.

The fourth resource mechanism for building a competitive advantage is knowledge in the form of information, for example on innovations or technology, which is highlighted by Bygrave (1987) and De Clercq and Dimov (2008).

A further extension of the RBV is the theory of dynamic capabilities. Dynamic capability refers to the capacity of a VCF to build, extend, or modify its current resource base and in this way achieve a competitive advantage (Teece et al., 1997, Helfat et al., 2009). As such, learning can be seen as a resource that is able to improve and adapt other resources. All VCFs screen, monitor and aid in operations. Different VCFs have differing levels of skill in implementing selection and treatment resources due to learning from prior experience (Barney et al., 2001). This disparity can allow VCFs to build a competitive advantage. De Clercq and Sapienza (2005) find that better portfolio company performance can increase learning. Their findings imply that this could lead to a vicious cycle, wherein the better VCFs attract better companies, learn more and gain higher levels of experience, and consequently attract even better companies. In this way, a company can build and maintain a competitive advantage.

In conclusion, it seems several treatment and selection resources of a VCF, including reputation, specialization, knowledge, contacts and learning, can all lead to outperformance. These are indicators of internal resources that can lead to a competitive advantage, as many of these resources are considered valuable and rare. In addition, these resources could also lead to a sustained competitive advantage as they are slowly built up over the years and most be considered as hard to imitate, non-substitutable and non-transferable. Treatment and selection resources can thus be seen as different types of resources at the disposal of the VCF in generating returns, consistent with the RBV.

2.2 The VCF Network as Proxy for External Resource Access

A VC network can be measured through its past syndication relationships (Hochberg et al., 2007; Bygrave, 1987), which occurs when multiple VCFs invest together by giving funding to a company in the same investment round. For a VCF, having a better network increases both the ability to syndicate and the ability to syndicate with better VCFs.

The following section displays that the network is in fact a proxy for, and thus captures, access to external resources. It is subdivided into two parts. The first part examines role of the network in gaining access to selection resources and the second part in gaining access to treatment resources.[1] Finally, alternative explanations besides resource access are inspected and the validity of the network as proxy for research access in this research is argued.

2.2.1 Access to External Selection Resources

Selection resources are the ability to select higher quality companies. This encompasses two components: screening, the skill of selecting better companies, and second, having a larger starting pool to select investments from (see Castanias and Helfat, 2001). Syndication improves the screening process by providing 'a second opinion' from other VCFs (see Lerner, 1994; Gompers and Lerner, 2004; Casamatta and Haritchabalet, 2007). By syndicating with others a VCF can check other VCF's willingness to invest, and combine different signals to select better investments. This is particularly beneficial in times of uncertainty on the feasibility or return, as multiple VCFs can choose better quality projects than a single VCF and reduce information asymmetries together.

For the sake of brevity, in the remainder of this section I predominantly focus on the three papers discussed below. The first two papers (Bygrave, 1987; Sorenson and Stuart, 2001) on are key works, commonly referred to in the body of network literature. The final paper De Clercq and Dimov (2008) has particular relevance to this study as it explicitly states a network as a means of gaining access to resources.

The work of Bygrave (1987) is an early study investigating the rationale of VCF syndication. This work is based on the resource exchange model. Data is collected from the early years of VentureXpert, taking a random sample of 1501 first round investments made by 464 VCFs from 1982 and before.

[1] As stated before, treatment and selection effects can be hard to disentangle from each other. For ease of understanding, I make a clear distinction on the one side of Bygrave (1987), Sorenson and Stuart (2001) and De Clercq and Dimov (2008), who focus mainly on selection resources, and on the other side Hochberg et al. (2015), who focus mainly on treatment resources. In practice however the former papers also partly take into account treatment effects, and the latter paper also takes into account selection effects even though the authors name it 'value-added' resources. Crucially this split does not impact the assumption that a network is a proxy for access to external resources.

Bygrave finds that networking is mostly due to uncertainty and the ability to share information, instead of the hypothesis of 'risk sharing': the spreading investment risk among multiple VCFs. Moreover, the more uncertain the environment is, the greater the extent of specialization of individual VCFs to obtain information, and therefore there is more syndication, to share such resultant specialized knowledge between VCFs.

Bygrave's work has two main implications for this study. First, he finds evidence of information being a resource, consistent with the RBV, and second, he finds that a network can be a means to access the resource of information. In conclusion, relating this work to Bygrave (1987), it could be that by drifting a VCF shifts into an area outside of their fund focus and will therefore be operating in an area they have less knowledge, with a greater level of uncertainty. Consistent with Bygrave (1987), VCFs with stronger networks might be able to undergo stage drifts more often if partners have specific knowledge on the area drifted to, as the risk of not having that knowledge internally is mitigated.

Sorenson and Stuart (2001) study venture capital networks and distance. The rationale behind their study is that in sociology, the probability of a personal relationship such as friendship decreases sharply as the distance increases. They argue that the same applies to venture capital, with distance equating to both geographic and industry distance, and information about investments circulating within such spaces. Information is defined along two dimensions, firstly the awareness of a possibility and secondly the quality of the information, which is be influenced by the trust a VCF has in the partner from the network. Sorenson and Stuart take the years of 1986 until 1998 from VentureXpert, with geographic distance measured by zip code and industry distance as the similarity between the portfolio company's industry profile and the VCFs prior investments. From this they compute three network variables: mean affiliation; the average count of the number of times each VCF has syndicated with the others, affiliate distance; the geographic distance between VCFs that already syndicated, and centrality in eigenvectors; measuring the quality of ties. Using a Bernoulli model to investigate the likelihood of a tie forming based on these coefficients, they find a negative significance coefficient for distance, meaning the larger the distance between two VCFs the less likely tie formation is. All interaction terms of the network and distance are positive, suggesting that VCFs with better networks are able to invest in more distant companies. Overall, they find evidence that a network can lead to a higher ability to invest in more distant geographic and industry options by accessing the resources of partner VCFs through the network. Their work is consistent with that of Bygrave (1987), as both find that information from partner VCFs can reduce the uncertainty surrounding an investment and lead to VCFs to increase their investment and screening possibilities through the network.

The work of Sorenson and Stuart (2001) provides indications with regard to stage drift. If a VCF is more specialized, by definition it invests less in options that are more distant from its area of specialization. For instance, a biotech-focused VCF most likely has a very high relative amount of investments in biotech, with few outside of that field. The authors find VCFs with better networks are more likely to invest in more distant options, and thus a biotech VCF with a strong network may be tempted to invest in a software company thanks to one its connections in its network. Their research thus provides clues that a stronger network could also lead VCFs to drift more.

De Clercq and Dimov (2008) look at venture capital from the RBV, in terms of knowledge. They are interested in internal knowledge development and external knowledge access in venture capital syndication relationships. They take U.S.-based, independent VCFs from VentureXpert, consistent with those used in my study. Their sample period spans from 1962 until 2002. They find that the effect of a VCF's knowledge, defined as the logarithm of the number of prior investments in that industry, becomes more significant when access to external partners is limited, showing that a VCF's internal knowledge is most important when investing by itself. Furthermore, when a VCF's knowledge is stronger, external partnering provides little to no benefit. When, however, a VCF lacks the knowledge needed in a particular area, collaborating with external partners with more industry expertise increases performance, as measured by a ranking of IPOs and M&A exits, and if a VCF was still private at the end of the study period. This lack of knowledge and skill outside a VCF's investment focus is in line with Wermers (2012), who demonstrates that skill is specific to the industry the VCF invests in. De Clercq and Dimov also look at the strength of these ties, namely at familiarity among syndicate members. Familiarity is measured as the number of times a VCF invested together with other syndicate members. They find that accessing external knowledge has a greater impact on performance for VCFs who have syndicated together before. In conclusion, Clercq and Dimov's (2008) work provides evidence that VCFs lacking knowledge can leverage their network in order to gain access to other VCF's knowledge, which is in line with the view this paper takes on the network as a resource in order to access to other VCF's resources.

2.2.2 Access to External Treatment Resources

With respect to treatment resources, VCFs have specific skill sets and knowledge that can reduce company specific risks when they intervene. The value added hypothesis (Gompers and Lerner, 1999), states that syndicates perform better because an increased number of VCFs can offer enhanced managerial support, a superior reputation, and a wider variety of contacts.

A large body of research focuses on access to treatment resources through the network. Wright and Lockett (2003) find that syndication is a way to access essential treatment resources. Through syndicating, VCFs can share complementary skills and knowledge, and thus add value to the portfolio company (Brander et al., 2002). If a VCF uses its treatment resources to help add value to a portfolio company, it also positively benefits the likelihood of other VCFs in the syndicate to achieve a higher return on their investment. Multiple VCFs can also offer better managerial support, a higher reputation, more diverse contacts and more industry expertise for their portfolio companies than an individual VCF (Gompers and Lerner, 1999; Chowdhry and Nanda, 1996; Andrieu and Groh, 2012). Finally, certification and reputation gains can be realized when syndicating with more experienced or different kinds of VCFs (Barry et al., 1990). This can convey a signal of quality of the company. At the exit, and in particular at an IPO, syndication can as a result lead to a higher price for the portfolio company.

In this section, I focus on the work of Hochberg et al. (2015) as a key underpinning study as in addition to De Clercq and Dimov (2008), it also explicitly states a network as a means of gaining access to resources. Hochberg et al. (2015) are interested in establishing why VCFs form syndication relationships with each other. They test two contrasting hypothesis: agency cost, that VCFs do not want to syndicate with different kinds of VCFs due to expropriation of resources and hold-up issues, and on the flip side resource accumulation, in which VCFs exchange resources among each other by syndicating. Data is on U.S. VC funds from VentureXpert, and covers a sample period of 1980 until 2003, tracking investment exits until 2009. They create four latent variables which could all lead to syndication, namely experience, network strength, available capital and investment scope (the latter how diversely a VCF invests across industries, geographies and stages). Subsequently, they look at the tie formation with probit and Tobit models, finding evidence for resource accumulation as resources indeed predict the likelihood of syndication relationships.

Their findings are key to this research as, they explicitly name a VCFs network as ‘access’, which they state is as a proxy for value-added resources. Also, their findings strongly suggest the network is in fact a proxy for resource access as different types of resources are in fact accessed through the network by being traded for each other.

2.2.3 Alternative Explanations of the Network

U.S. research on syndication has predominantly found evidence that resource sharing, corresponding with the view of this work, is the key reason behind syndication (Bygrave, 1987, 1988; Norton and Tenenbaum, 1993). However, to completely exclude the option of alternative theories I also present alternative views of using the network. There are two alternative reasons for VCFs to syndicate (De Clercq and Dimov, 2004). The first is the risk-sharing view; risk-sharing means that VCFs can diversify their risk and decrease their exposure to volatility in individual investment areas by investing together. The second is the deal-flow motive, whereby there is an element of reciprocity. By inviting a VCF into a deal today, they in turn they hopefully reciprocate with an investment opportunity in the future.

In a U.S. based sample, De Clercq and Dimov (2004) find that in addition to resource sharing, risk-sharing and deal-flow motives are of importance, but they rule out risk sharing motives for earlier stage companies.

In more recent European work by Manigart et al. (2006) and Lockett and Wright (2001), resource access is considered less important than the other two factors. It is worth noting that both papers are based on VCFs in European countries, which have been shown in to behave differently from U.S. VCFs as the market is less liquid and developed, and syndication is less frequent (Schwienbacher, 2005). In their research, Lockett and Wright (2001) therefore also explicitly contrast their findings against syndication motives in U.S. syndication research. In addition, Manigart et al. (2006) openly state that use of a European VCF sample may lead to different results than U.S.-based studies, as risk-sharing motives may be more important to European VCFs. The latter authors also suggest that lead and non-lead VCFs could have different syndication motives, but only find evidence that for deals in which a given VCF is the non-lead the reason for joining a syndicate is due to access to resources. In this study I therefore take into consideration networks in which the VCF is a non-lead VCF in my models, and results display evidence in line with the network as proxy for resource access.

The reciprocation motive in our sample can be ruled out when for the non-lead network measure, as when VCFs are joining deals they are not giving opportunities to other VCFs in hope of reciprocation.

In conclusion, considerable evidence has been found demonstrating that the network leads to access to information (Bygrave, 1987; Sorenson and Stuart, 2001; De Clercq and Dimov, 2008), as well as access to various treatment resources (Brander et al., 2002, Hochberg et al., 2015).

2.3 Style Drift

The following section outlines the possible causes of style drift and if this could be done due to resource access. Style drift is a major topic of interest in mutual funds, and is predominantly viewed in terms of the risk shifting (e.g. Brown et al., 1996; Hu et al., 2011; Kempf and Ruenzi, 2008; Qiu, 2003; Schwarz, 2013). Therefore, in the following section I describe the major causes of mutual fund drift in order to establish the concept, and afterwards discuss stage drift and venture capital.

2.3.1 Style Drift in Mutual Funds

2.3.1.1 Risk Shifting due to Agency Theory: Employment Risk and Compensation Incentives

Agency theory is when an agent to makes decisions on behalf of the principal, but is motivated to act in his own self-interest (Eisenhardt, 1989). For an investment fund this refers to the fund (the agent), investing differently than optimal for the LPs (the principal), in order to benefit themselves. Agency theory can be divided into adverse selection, the misrepresentation of the ability of the agent, which takes place before an agreement is made, and moral hazard, the suboptimal behavior by the agent, which comes after an agreement is made (Eisenhardt, 1989).

The work of Brown et al. (1996) fits the moral hazard framework. They are the first to investigate whether fund managers alter their risk levels based on mid-year performance rankings, and consider whether this kind of behavior can be fitted into a tournament type view of the industry. They look at Morningstar funds between 1976 until 1991, and use growth funds as these are well followed and in general take riskier positions. Returns are looked at between each month and January, and ranked from highest to lowest based on halves and quartiles. Their findings fit their predictions of moral hazard, and fund managers act in their own interest at expense of the LPs. Fund managers that are losers in the month of July, when the financial press report interim rankings, shift to higher risk investments, and winners in July take less risk. They find that funds that risk shift underperform. In conclusion, their paper finds that style consistency is important in choosing managers, as risk shifting signals future underperformance and fund manager inadequacy.

Since Brown et al.'s (1996) work, scholars have since built upon this tournament structure. One of these, Qiu (2003), finds that the tournament structure does not hold and offers a new labor-centered perspective on risk taking. He looks at three fund types, aggressive, long-term growth, and income & growth oriented, but finds no difference among the groups. His work can be split into three topics: termination risk the (risk shifting due to possibility of a manager losing his job if performance is poor), flow-induced compensation incentives (risk shifting to gain additional capital), and multiple managers. In contrast to Brown, he finds that losers, defined as those with below the median returns, actually shift into less risky strategies due to fear of losing their job. Furthermore, the 'winner takes all' structure of being the best, and thus gaining hefty fund inflows, makes funds at the very top shift towards lower risks in order to maintain their position, while simultaneously funds just below that point actually shift into riskier strategies.

In addition, Qiu (2003) finds that multiple fund managers, whether winners or losers, take fewer risks than single managers, and thus drastically reduce agency costs across the board. For losers in the lowest quartile the biggest difference is noted, at approximately 40%. It is quite common for mutual funds have a single fund manager, whereas in VC funds are for the large part run by multiple managers (Wright and Lockett, 2003). Conversely, stage drifts are still frequent for VC funds (Cumming et al., 2009).

Hu et al. (2011) look at employment risk. They explicitly find a U-shaped relation between taking risk and prior performance, meaning that significantly outperforming managers are less likely to be fired and therefore take more risks, but also that significantly underperforming managers take on more risk. Furthermore, they combine and confirm a number of theories from prior research in other areas of mutual funds regarding the concept of risk shifting. They find evidence that younger managers, funds with higher expense ratios and bigger fund families all have less a less convex U-shape relationship between risk and prior performance, and therefore have lower incentives to engage in risk shifting. For younger managers this effect can be explained by higher employment risk, and for expense ratios this could be due to higher marketing expenditure, which would lead to less sensitivity to fund inflows.

Wermers (2012) studies style drift in mutual funds as well. Data is collected by merging the commercial databases Thomson, CRSP, and Morningstar for the period of 1975 - 2000. He looks at two alternative views, on the one hand the 'specialization hypothesis', which states that funds build resources in a certain sector, and on the other hand the 'generalist hypothesis' which views managers talent in identifying under-priced stocks as not limited to their own style, but applicable to all stocks in general. Wermers builds upon the work of Brown et al. (1996), but adds several extensions. He splits style drift into active and passive drift, where active drift is intentionally taken by the fund manager and passive drift is a change is style resulting from passively holding a portfolio. Subsequently, instead of only analyzing one dimension, drift is defined along three dimensions, namely size, value, and momentum. He takes five fund types from income/balanced to aggressive growth and maps out the drift in each category, as opposed to only including growth funds, done in Brown et al. (1996). His findings are as follows: first, momentum is the biggest cause of style drift. Additionally, active management also leading to an increase. Moreover, growth funds, smaller funds and managers with good previous performance all drift more and outperform after trading costs. Both passive and active style drift outperform, and the top 10 percent showing active style drift beat their style benchmarks by more than three percent by year. His results are therefore consistent with the generalist hypothesis.

2.3.1.2 Risk Shifting due to Market Conditions

Similarly, to scholars before them, Kempf and Ruenzi (2008) look at employment risk and flow-induced compensation incentives, but focus on whether these change in response to bull and bear market phases. Crucially, they divide risk shifting into an active and a passive component, which they call unintended and intended risk, which is an approach also followed at a later point in time by Wermers (2012). They control for unintended risk by comparing expected versus realized risk levels and find that fund managers adjust for these risk surprises mid-year based on risk targets. After controlling for unintended risk, they find that losers take much greater risks in bull markets due to flow-induced compensation, and fewer in bear markets due to employment risk, with the effects being stronger for more extreme market periods. Their work thus reconciles the apparent contrasts between the conclusions of Brown et al. (1996) and Qiu (2003), displaying that the effects found by each paper can exist simultaneously, due to risk shifting being dependent on market cycles.

Schwarz (2013) also looks at tournaments but critiques the sorting of previous literature on returns and risk simultaneously, stating that this is erroneous as risk and return tend to go together. The implication is that such studies find evidence of a tournament, when in fact funds means revert in order to meet risk levels at the end of the year. His proposed solution is to look instead at portfolio holdings. Consequently, his work is similar to that of Kempf and Ruenzi (2008), who also look at portfolio holdings and risk levels. Both also collect data from the same sources, CRSP and Thomson. However, the methodology differs in that Schwarz (2013) controls for mean reversion due to non-risk motivated trading by not using the actual portfolio for the baseline risk level, as in Kempf and Ruenzi (2008), but by bootstrapping to extrapolate how a non-risk motivated manager would behave in the second half. Surprisingly, his new methodology leads him to directly contradict the view of risk shifting due to different market conditions of Kempf and Ruenzi (2008), and he finds market conditions are not significant after controlling for sorting. Instead he finds evidence that fund managers who underperform in the first half shift to higher risks, consistent with Brown et al.'s (1996) original tournament model, and contrary to the ideas of Kempf and Ruenzi (2008) that employment risk causes a decrease in the risk taking behavior of underperforming managers.

In conclusion, mutual fund literature generally agrees that previous performance leads to risk shifting through the agency costs of fund-inflow incentives and employment risk. The implication of these theories are generally consistent with each other, with Brown (1996), Schwarz (2013) finding losers take on more risk and winners less, while Qiu (2003) finds that funds right under the top performing funds take on much more risk, and Hu et al. (2011) demonstrating that both significantly outperformers and underperformers take on more risk. Market conditions seem to have an effect on risk shifting of past outperformers and underperformers (Kempf and Ruenzi, 2008), but conversely, after sorting, it is uncertain if they actually affect the risk shifting attitude of funds (Schwarz, 2013).

2.3.2 Style Drift in Venture Capital

VC style drift has to my knowledge currently only been able to be examined in terms of stage drifts, and not geographic and industry drifts, due to the nature of the available data (Buzzacchi et al. 2015; Cumming et al., 2009).

The previous section studied mutual fund style drift. In mutual funds, investments are relatively liquid. Style drifts can be performed during the middle of the year and impact performance at the end of the same year. In contrast, VC investments usually take five years or longer to exit. The investment and exit stage are usually separated, with the first three years of the fund usually spent on investment, and the subsequent years focused on adding value to the portfolio companies and achieving exits (see Hochberg et al., 2007). Therefore, the concept of shifting into riskier investments halfway through the investment stage as applied in the work of Brown et al. (1996) is less likely, and thus style drift takes on distinctive traits in venture capital. Research in this area within the context of venture capital is severely limited. The current state of research in venture capital defines drifts as either being done due to agency theory or market conditions, which are examined in the following section, and which are comparable motives to those in mutual funds. In the final section covenants are briefly examined.

2.3.2.1 Stage Drift due to Agency Theory

Cumming et al. (2009) look at U.S. private equity (PE) investments. They build upon the work of Kempf and Ruenzi (2008) and look at active stage drift by taking only the first funding round, establishing causes and effects of stage drift. In particular, they construct a theoretical two stage model, with a principle and an agent, in which they predict that younger fund managers will undertake stage drift less often due to adverse selection, and thus want to signal their screening ability within their stated objectives to LPs. Their work is thus aligned with agency theory literature, but instead of focusing on moral hazard focusses on adverse selection. They model stage drift within a cost benefit framework, where on the one hand stage drift can benefit performance, but on the other hand can lead to reputation loss. For their data they use the VentureXpert database and create a sample of 11,871 non-generalist first round investments into U.S. companies from 1985 until 2003. Stage drift is defined by a dummy variable equal to one when a fund manager invests in a different stage than his fund focus. They find that younger PE VC funds with a shorter track record drift less due to higher reputation costs of deviation, and that investments which experience a drift by the VC fund have an increased probability of an IPO exit. Wermers (2012), who examine previous performance as well as a fund's experience, find no significance of experience on style drift, which contrasts Cumming et al. (2009). It is thus possible that the effect of experience found by Cumming et al. (2009) acts as a proxy for the variable of previous performance.

The work of Buzzacchi et al. (2015) examines risk shifting in venture capital and relate this to managerial incentives and past performance. Instead of defining drift as being consistent or inconsistent with the funds stated focus, they define drift into higher and lower stages of investment as taking on a different amount of risk. Style drift into a higher stage of development is defined as less risky, as a more mature company is also more likely to obtain a successful exit. Style drift into a lower stage of development is defined as the opposite, namely as taking on more risk. Their dataset comprises 1,925 investments by 149 VC funds from 1998 until 2007. Data is from the European Investment Fund (EIF), and consequently all VC funds in the sample, received funding from the EIF, an organization which specializes in SME equity financing. This institute is largely owned by the European Investment Bank (62.1%) and the European Commission (30%). The remaining shareholders are public or private banks, and financial institutions (7.9%). In contrast to the work of Cumming et al. (2009) on adverse selection, Buzzacchi et al. focus on moral hazard. For their dataset they find evidence that indicates that a higher hurdle rate leads to fund managers less willing to take on less risks (as defined by upward drifts) in line with the fund inflow incentives of mutual funds (Brown et al., 1996; Qui, 2003; Hu et al., 2011; Schwarz, 2013). Furthermore, VC funds higher management fees (which they dub as reputation) are to less likely to upward drift and more likely to downward drift, showing that managers with a higher reputation play it safe. Furthermore, they find that previously underperforming funds are less likely to perform upward drift than previous outperforming funds and that this effect is stronger in times of bull markets, in line with Kempf et al. (2009).

There are numerous differences between Buzzacchi et al. (2015) and this research. Firstly, their work is on European data. European funds have been shown to behave very differently than U.S. funds (Schwienbacher, 2005), which can lead to different effects regarding stage drift. Also, since they use European data, they control for the different European countries in their data, which is less necessary in this research as the states in the U.S. are a more homogeneous market. Secondly, past performance is defined as the amount of write-offs, defined by IRR data, over the total number of previous deals. I do not have IRR data, but the approach of taking successful exits over the total investments such as in Hochberg et al. (2007) is very similar. Thirdly, Buzzacchi et al. (2015) include non-independent type of funds in their data. They do not specify what percentage of their funds are bank, corporate or government owned. Mainly, their data includes governmental VC funds, with about 20% of VC funds receiving more than half of their funding from government institutions and approximately 60% of VC funds having 10 – 50% of governmental LPs. A lot of work has displayed the difference of government versus independent funds (Brander et al., 2008; Lerner, 2009), as different investment objectives are regarded superior to performance, such the growth of a community or to increase work in a region, which consequently can lead to a different method of investing. With regards to stage drift Cumming et al. (2009) exclude these type of funds due to these reasons, and furthermore state that these funds can have very different investment objectives and do not have limited durations. Hence, including funds which are heavily influenced by the IEF or other governmental institutions as the main or largest shareholder, can lead to pressure to invest funds differently which can lead to completely different conclusions regarding stage drift than pure independent funds. The authors do however present the findings regarding past performance and market conditions for funds of which ownership is more than 50% by the public LPs. The results of this approach do not change the findings. However, no similar methodology is taken regarding their findings of the management fees and the hurdle rate. Fourthly, unlike Cumming et al. (2009), Buzzacchi et al. (2015) only control for the stage of development and they do not control for industries in their regressions, which might be due to their data source. The industry in which a company operates is included and also a rather significant control variable in this research. Finally, the distinction between active and passive stage drift is crucial, as the two can have very different interpretations. The authors do not mention if they split their sample into active and passive stage drift, which is done in this research as well as Cumming et al. (2009).

2.3.2.2 Stage drift due to Market Conditions

Nanda and Rhodes-Kropf (2013) only look at seed and early stage firms and do not look at stage drift or style drift; however, their work touches on the concept, as they investigate whether the investment style of a VC fund changes depending on a hot cycle as measured by the logarithm of the number of VCFs financed in the same quarter, which captures the availability of funding resources for VC fund. They do not look at returns, as in prior research, but instead look at the variance in returns of companies funded in hot cycles, examining at IPO proceeds and at the number of patents and citations a VCF has. Data is retrieved from the Dow Jones Venture Source and is on U.S.-based startups from 1985 to 2004, tracking company exits until 2010. The sample is composed of 12,285 seed and series-A VCFs. A key measure they control for is the pre-money valuation, which is the value of the company immediately prior to the IPO. They state that as portfolio companies raise different amounts of money at the IPO, the pre-money valuations allow for a fairer comparison across portfolio companies. However, since VentureXpert has very limited pre-money valuation data, I am unable to take this aspect into account in my own data selection. For VC early stage investments Nanda and Rhodes-Kropf (2013) display that when there is more capital available, VCFs shift their investments into riskier, more innovative companies, and that this is especially true for more experienced VCFs, who perform better in these markets. This is consistent with Cumming et al. (2009), who also show drift is performed by more experienced VCFs.

Again, the authors do not mention style drift, and it is not possible to establish whether style drift could be driving the majority of their results. However, it seems that VCFs take on more risk in hot markets, which could be due to style drift into different areas of investment focus, consistent with the above findings of Cumming et al. (2009).

In their work Cumming et al. (2009) also find that market conditions for VC funds, as defined by an increase in the Nasdaq index, decrease the chance of stage drift for early stage funds while increasing the chance of stage drift for later stage funds. The Internet bubble, which led to a big increase in the Nasdaq, has a similar effect. Periods when the stock market is doing better are often coupled with greater capital availability of capital for VCFs (Hochberg et al., 2007). It is thus highly possible that the increase in the Nasdaq of Cumming et al. (2009) acts as a proxy for the availability of capital in the data used by Nanda and Rhodes-Kropf (2013).

In conclusion, stage drifts can be carried out due to agency theory or market conditions. Cumming et al. (2009) find that as the experience resource increases so does drift, consistent with agency theory on mutual funds (Hu et al., 2011). Buzzacchi et al. (2015) find that VC funds with a higher hurdle rate and reputation are less likely to upward drift, and more likely to more downward drift. In addition, they find evidence of agency costs with respect to past performance, and also past performance interacted with market conditions. Regarding market conditions, Cumming et al. (2009) find that later stage funds drift more when the market has increased whereas earlier stage funds drift less. Nanda and Rhodes-Kropf (2013) find that capital availability can lead VCFs to risk shift more to riskier and more novel startups. All papers do not look at network resources, but it is highly plausible that if market conditions can lead funds to drift more, then network resources can have a similar effect.

2.3.2.3 Prevention of Style Drift by Limited Partners

Venture capital partnership agreements are structured between investors, called limited partners, and the fund managers, called general partners (GPs). The LP supplies capital and the GP executes investment decisions (see Cumming et al., 2009), with the topic of style drift forming part of the interaction between these parties. Prior work on covenants between LPs and GPs by Gompers and Lerner (1996) has demonstrated that there are more covenants when agency costs are higher, for instance with younger companies, earlier stage companies, and companies in more high tech industries. Nonetheless, supply and demand also play a role; when a lot of money flows into the VC industry or when a VC fund can demand high compensation, there tend to be fewer covenants. Therefore, it could be that in better market conditions, or for certain industries or stages VC funds drift more. Gompers and Lerner's (1996) work on covenants can be compared to that of Wermers (2012), who finds that style drift is undertaken in the mutual industry for exactly the types of funds which the authors find are more prone to agency costs, namely growth companies and smaller funds. The latter are most likely to be younger and thus less experienced, highlighting that in VC, covenants are indeed done in agency costs prone areas.

As Hu et al. (2011), Cumming et al. (2009), and Wermers (2012) find that younger, smaller, and growth companies can show different patterns, I accordingly control for age, fund size and the stage of VC funds. It seems although style drift occurs frequently, covenants are used to prevent style drifts (see Cumming et al, 2009). Intriguingly, the work of Gompers and Lerner (1996) offers an alternative explanation to the theory that market conditions can lead to style drift as proposed by Cumming et al. (2009) and Nanda and Rhodes-Kropf (2013), as weaker covenants in times when there is more money flowing into the VC industry can facilitate style drift. Although I do not control for covenants, I investigate the possibility of market conditions and fund inflows having an effect on VC drift.

3. RESEARCH QUESTION AND HYPOTHESIS DEVELOPMENT

A VC fund with a stated stage focus is likely to have greater treatment and selection resources for that particular stage relative to other stages. Partner VC funds with whom the VC fund syndicates with can also have high screening and/or treatment resources *outside* of a VC fund’s stage focus. A network can lead to a fund access to other funds resources (Bygrave 1987; Sorenson and Stuart, 2001; De Clercq and Dimov, 2008; Hochberg et al., 2015), and resources are essential for a fund, as funds with more resources enjoy outperformance (e.g. Hochberg et al., 2007; Nahata, 2008). Therefore, a VC fund with more access to other VCF’s resources is more likely to be able to access beneficial resources outside its stage focus, and is subsequently going to become more capable of investing outside its stage focus. Accordingly, the risk-adjusted payoff of investments outside its stage focus is going to increase. If this level exceeds the expected risk-adjusted payoff of possible investments within a VC fund’s stage focus, I expect the VC fund to drift. Consistent with these predictions, I formulate the following hypothesis:

H1: *VC funds with a higher access to external resources downward drift and upward drift more*

Mutual fund literature has found a tournament effect (Brown et al., 1996; Qui, 2003; Hu et al., 2011; Schwarz, 2013), wherein managers compete for fund inflows. Previous research into this topic has generally shown consistent findings. Brown et al. (1996) and Schwarz (2013) find that underperforming fund managers in the first period will increase their risk in the second period, in order to improve their position against other managers. Funds have less to lose from a further decline in their position with regard to fund inflows and compensation, while they have much more to gain from taking on more risk in order to catch up with mid-period winners. Consistent with this, Buzzacchi et al. (2015) find that managers of poorly performing VC funds increase their fund's risk by upward drifting less, relative to managers of VC funds with good past performance. This leads me to the following hypothesis:

H2: *VC funds with poorly (better) past performance are likely to downward (upward) drift*

Kempf and Ruenzi (2008) study different market conditions and find that find that in a bull market compensation incentives are likely to dominate, and consequently poorly performing funds increase their risk more than better performing funds. However, in bear markets employment incentives are more prominent and poorly performing funds actually increase their risk less than better performing funds. In accordance with Kempf and Ruenzi (2008), Buzzacchi et al. (2015) find that poorer performing VC funds upward drift less during bull markets, thus taking less risk.

Both Kempf and Ruenzi (2008) and Buzzacchi et al. (2015) take the U.S. stock market data as a proxy for fund inflows. However, the public market in which mutual funds operate is different from private markets. Increases in the public markets do not necessarily capture increasing funds into private markets, in which venture capital operates. Therefore, I directly measure VC industry inflows instead of taking a public market measure. It follows that:

H3: *When there are more fund inflows downward (upward) drifts are more likely for (better) poorly performing VC funds*

4. DATA AND METHODOLOGY

4.1 Data Sample

The data for my research was accessed through VentureXpert, also known as the Thomson Financial Venture Economics database. Together with VentureOne, this is the leading database used by researchers studying venture capital. Data in this database is self-reported by VCFs or by portfolio companies that receive investment.[2]

Most VC funds are structured as 10-year limited, closed-end partnerships. A fund usually takes three years to select companies to invest in, which then support them over the next seven years (Ljungqvist et al., 2005; Gompers et al., 2006). In the second half of the fund's lifetime, portfolio companies are exited via an IPO or acquired by companies. At the end of the fund's lifetime, the remaining holdings are either sold or liquidated. Data entry in VentureXpert started in 1977, with data from the early 1960s later added. Due to data quality concerns, however, this early data is often not usable (Gompers et al., 2004). In line with Hochberg et al. (2007), I drop data from before 1980. The sample period ends in 2010, leaving approximately five years for exit data. The dataset thus spans from 1975 – 2010, with investment exits tracked until 15 March 2016.

After defining my timeframe, excluding angel investors and individuals,[3] (consistent with Hochberg et al., 2007) as well as non-private equity deals, the data contains 286,836 observations. Ample previous venture capital research has focused on the United States due to the comprehensiveness of available data (Nanda and Rhodes-Kropf, 2013) and I therefore only include investments from U.S. VC funds which makes the observations drop to 192,249.[4] From this 'full' dataset I construct different measures of networks and both VC fund and VCF characteristics.

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[2] VentureXpert data oversamples Californian companies and larger rounds. It excludes about 15% of the financing rounds and 20% of committed financing. However, these omissions in VentureXpert do not lead to selection bias (Kaplan et al., 2002). I can thus assume I have a random sample, but nevertheless I include a dummy for companies based in California and Massachusetts, to reduce a potential sampling bias.

[3] Angel investors and individuals are a different type of group that is best studied separately (Chemmanur & Chen, 2003).

[4] In this respect I differ from Cumming et al. (2009) in VC drift literature, as they are mostly interested in drift on the company level and does not look at it from a fund perspective. I take all US funds (in line with Hochberg et al., 2008 who also look at the fund perspective instead. Taking only US companies would create a bias in funds that invest a lot outside of the US, as these investments are not counted in their investment experience and network centrality.

From this full dataset, I establish a ‘primary sample’, following Cumming et al. (2009) to limit my sample to first-round investments in order to only look at active stage drift by excluding the passive stage drift that results from a lack of rebalancing of the portfolio over time. Furthermore, stage drift can only be measured if the fund has communicated a certain stage focus to LPs, so it does not apply to generalist funds. Finally, I drop all VCFs which are government, corporate or bank operated, as drift is of primary concern in the relationship between LPs and GPs, and non-independent VCFs can have very different objectives. This leads to a final sample of 12,999 investment observations from 10,447 companies, with 2,900 VC funds and 1,401 VCFs.

Table 1 reports the occurrence (and corresponding percentages) of the stage focus of VC funds and the actual development of the entrepreneurial companies in the sample. While the majority of VC funds have an early stage commitment (75.7%) and a large amount of companies are in an early stage of development (44.4%), the data show that stage drift is not a trivial occurrence and takes place at all stages of development. Stage drift is most prominent for seed stage VC funds investing in early stage companies (39.4%), early stage VC funds investing in seed stage companies (30.8%) and later stage VC funds investing in early stage companies (28.4%). Table 2 presents the occurrence (and corresponding percentages) of stage drift for the sample. Approximately 50% of deals are drifts, of which 20.40% are upward drifts and 29.93% are downward drifts.

Table 1:

Fund Stage Focus and Stage of Development of Entrepreneurial Companies

This table presents the occurrence (and corresponding percentages) of stage drifts (and non-drifts) for the sample of VC funds for the period 1980 – 2010. The sample includes all VC funds that indicate a focus on a particular stage of development and excludes generalist and balanced funds that do not focus on a specific stage of development.

		Company development stage			
		Seed stage	Early stage	Later stage	Total
Fund stage focus	Seed stage	512	433	154	1,099
		(46.59%)	(39.40%)	(14.01%)	(100%)
	Early stage	3,025	4,737	2,058	9,820
		(30.80%)	(48.24%)	(20.96%)	(100%)
	Later stage	274	582	1193	2,049
		(13.37%)	(28.40%)	(58.22%)	(100%)

Table 2:

Occurrence of Stage Drifts

This table presents the occurrence (and corresponding percentages) of both upward and downward stage drifts for VC funds for the period 1980 – 2010. Upward drifts exclude funds with a focus on later stage investments, while downward drifts exclude funds with a focus on seed investments. The sample includes all VC funds that indicate a focus on a particular stage of development and excludes generalist and balanced funds that do not focus on a specific stage of development.

		Drifts	Upward drifts	Downward drifts
Fund stage focus	Seed stage	587	587	n.s.
		(53.41%)	(53.41%)	
	Early stage	5,083	2,058	3,025
		(51.76%)	(20.96%)	(30.80%)
	Later stage	856	n.s.	856
		(41.78%)		(41.78%)
	Total	6,526	2,645	3,881
		(50.32%)	(20.40%)	(29.93%)

Table 3:

Sample Descriptive Statistics

This table presents the variables of the sample of VC funds for the period 1980 – 2010. *Company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *VCF age* is measured as the amount of years between the first investment made by the fund and the first investment made by the fund's parent. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. *Fund size* is the amount of capital committed reported in the VentureXpert database. *ln experience companies* is measured as the logarithm of the total amount of companies invested in between the parent's first investment until the given investment date. *ln experience invested dollars* is captured by the logarithm of the aggregate dollars invested between the parent's first investment until the given investment date. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *Reputation* is the VCFs share of the IPO market, from 1980 until the date of investment, determined by the cumulative market capitalization of the dollar value of all companies taken public by the VCF, relative to other VCFs. *=1 if bull market* is a dummy variable which is equal to one the Nasdaq composite index went up during that calendar year, and zero otherwise. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *% increase Nasdaq* is the increase in the Nasdaq composite index between the first investment made by the fund and the current investment date. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Mean B/M* is the book-to-market ratio of public companies in the industry and year of investment and has not been included in the model except as interaction variable with *past performance* due to multicollinearity issues. *Downward stage drift* has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. *Upward stage drift* is equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. *Lagged downward drift rate* is the downward drift rate of the VC fund of all investments ten years prior to the current investment date. *Lagged upward drift rate* is the upward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network.

	No.	Mean	Std. Dev.	Median	Min	Max
Company and investment characteristics						
Company age	10746	1.27	1.90	0.59	0.00	11.79
ln amount invested by syndicate	12159	0.30	1.45	0.42	-7.26	3.21

(continued)

Table 3 - *Continued*

	No.	Mean	Std. Dev.	Median	Min	Max
Number of VC funds in syndicate	12968	3.08	2.06	3.00	1.00	11.00
=1 if company from California	12968	0.37	0.48	0.00	0.00	1.00
=1 if company from Massachusetts	12968	0.09	0.29	0.00	0.00	1.00
=1 if lead VC fund	12968	0.20	0.40	0.00	0.00	1.00
VC fund and VCF characteristics						
=1 if first fund	12968	0.28	0.45	0.00	0.00	1.00
VCF age	12968	5.12	6.76	1.67	0.00	25.97
Fund sequence	12968	3.40	3.40	2.00	1.00	25.00
Fund size	10031	152.10	219.35	61.00	0.40	1175.00
ln experience companies	12968	3.07	1.58	3.14	0.00	6.02
ln experience invested dollars	12968	3.78	2.29	3.93	-3.69	7.79
Past performance	8891	0.39	0.28	0.33	0.00	1.00
Reputation	12919	0.30	0.60	0.02	0.00	3.16
Fund inflows and market conditions						
=1 if bull market	12968	0.66	0.47	1.00	0.00	1.00
=1 if during the dotcom bubble	12968	0.25	0.44	0.00	0.00	1.00
=1 if during the subprime mortgage crisis	12968	0.09	0.28	0.00	0.00	1.00
% increase Nasdaq	12968	1.02	3.17	0.16	-0.58	22.24
ln VC inflows	12968	4.18	1.25	4.57	0.60	5.66
Mean P/E	12968	22.84	9.16	22.41	-6.80	60.90
'Past performance' * '=1 if bull market'	8879	-0.02	0.22	0.00	-0.39	0.61
'Past performance' * '=1 if during the dotcom bubble'	8879	0.04	0.16	0.00	-0.39	0.61
'Past performance' * '% increase Nasdaq'	8879	-0.01	0.47	0.02	-6.54	5.98
'Past performance' * 'ln VC inflows'	8879	-0.04	0.38	-0.01	-2.26	0.98
'Past performance' * ‘Mean B/M'	8879	-0.00	0.06	0.00	-0.30	0.56
'Past performance' * ‘Mean P/E'	8879	0.18	2.63	0.08	-15.54	23.41
Drift measures						
Downward drift	12968	0.30	0.46	0.00	0.00	1.00
Upward drift	12968	0.20	0.40	0.00	0.00	1.00
Persistence						
Lagged downward drift rate	11367	0.32	0.27	0.29	0.00	1.00
Lagged upward drift rate	11367	0.21	0.24	0.15	0.00	1.00
Resource access measures						
Degree	12968	2.39	3.06	1.15	0.00	15.44
Outdegree	12968	2.76	4.79	0.74	0.00	28.29
Indegree	12968	2.19	3.22	0.93	0.00	17.53
Eigenvector	12968	5.19	6.05	2.72	0.00	28.20
Betweenness	12968	0.37	0.75	0.09	0.00	4.75

4.2 Variables

4.2.1 Company and Investment Characteristics

Not all companies are created equal, and certain companies are more promising than others. When analyzing companies in aggregate, certain company characteristics can be more prone to a successful exit, or if a VC fund sees certain characteristics as more desirable, more prone for a VC fund to drift to. Therefore, in accordance with Cumming et al. (2009) I control for the age *(company age)* of the company at the time it receives financing and the total amount invested by all syndicate members *(amount invested by syndicate)*. In accordance with De Clercq and Dimov (2008), the quantity of VC funds financing the company (*number of VC funds in syndicate*) is controlled for as well as whether the VC fund is the lead VC fund (*=1 if lead VC fund*) in this particular investment.

In addition, following both Cumming et al. (2009) and Hochberg et al. (2007) I create 'dummies' for the industry and the stage of development the company. As the VentureXpert database oversamples data from California and Massachusetts, I also create a dummy for companies that come from either of these regions *(=1 if company from California,* or *=1 if company from Massachusetts)*. Table 3 puts forward these, and the other sample variables with their descriptive statistics.

4.2.2 VC Fund and VCF Characteristics

I) Experience

It is common practice to control for fund and VCF characteristics (Hochberg et al.; 2007 Cumming et al., 2009; Nahata, 2008). Experience has been shown to influence the performance of a fund in a positive way (Kaplan and Schoar, 2005). Accordingly, it is very likely that more experienced VCFs also have bigger networks (Hochberg et al., 2007). Here, I correct for different experience measures to ensure the network does not act as a proxy for a higher level of experience.

The first measure I construct which proxies for investment experience is the *fund sequence* (Cumming et al., 2009). Since VentureXpert does not specify the sequence of a fund besides stating if it is a first time or a follow-on fund, I construct the sequence number of the fund from my full sample, which can be viewed as a type of experience measure for a fund. In addition to *fund sequence*, it can be that a first time fund has an additional effect on drifting (Cumming et al., 2009). I accordingly add a dummy variable if VentureXpert reports the fund as a first time fund *(=1 if first fund)* (Hochberg et al., 2007). I then measure the age of the VC fund from the parent's first investment[5] to the given investment date *(VCF age)* (Cumming et al., 2009). The fourth measure used is the aggregate amount of dollars the parent has invested *(experience invested dollars)* between the VCF's first investment and the given investment year

[5] VentureXpert often does not correctly measure the founding date of a fund. Using a VCFs first date of investment more accurately maps out the true date at which the fund was founded.

(Hochberg et al., 2007). The number of portfolio companies in which parent has invested in so far *(experience companies)* (Hochberg et al., 2007), also measured between the VCFs first investment and the given investment year, forms the fifth measure. Finally, funds in different stages can have different probabilities of drifting (Buzzacchi et al., 2015; Cumming et al., 2009). I therefore further control for the development stage of the fund, consistent with Buzzacchi et al. (2015).

II) VCF Reputation

It can be that experience, network and reputation all measure the same effect, namely of a more successful company. To ensure that my results are really driven by a network, and do not merely capture unobserved effects from a VCF's reputation, I also include a measure for reputation. Nahata (2008) proposes a measure which captures the reputation of a VCF as measured by the IPO capitalization share. I construct a measure called *reputation* accordingly. For each VCF I add the dollar market value of all companies which have been taken publically by the VCF since the beginning of 1980 until the given date of investment and normalize it with the aggregate market value of all VC portfolio companies that went public from 1980 until the given date. The market value of portfolio companies is determined by the initial day closing price and the number of shares outstanding, both of which come from the Center for Research in Security Prices (CRSP). I depart from the methodology used by Nahata by examining reputation on a daily basis, instead of per year. For example, for investments which receive funding on December 31th 1982, the reputation measure is based on approximately three years of data, as the data starts at January 1st 1980, and goes until the day before the investment is made, which is December 31st 1982. For investments made on March 2nd 1990, the reputation measure is based on data from January 1st 1980 until March 2nd 1990.

III) Fund Size

The size of a fund has been shown to positively influence the performance (Kaplan and Schoar, 2005). I therefore create a variable for the total size of the venture fund size (*fund size)*, which is the amount of capital committed reported in the VentureXpert database. A little less than a quarter of data on the fund size is missing from the dataset.

IV) Past Performance

In the ideal scenario, I would directly measure the fund performance of a VC fund and its portfolio companies. However, since investments are in private corporations and not public, returns are not always available and VentureXpert does not disclose fund returns for individual VC funds or companies. Regarding fund performance, VC funds gain most of their profits from the few investments that either have an IPO or are acquired (Nahata, 2008). Therefore, I measure fund performance indirectly, a well-accepted method in venture capital research also used by Gompers and Lerner (2000), Hochberg et al. (2007), Sorensen (2007) and Nahata (2008), and which matches data from the SDC New Issues database and the SDC M&A database to obtain exits corresponding to the investments.[6] All exits until the 15th of March 2016 are taken into account.[7]

I successfully match 24% of companies in my full sample. Hochberg et al. (2007) report an exit rate of 34% over their sample period from 1980 to 1999; my dataset that encompasses the same period shows a reduced exit rate of 31%, highlighting that the difference in exit rate is due to a significantly reduction in recent years (2000 until 2010). In my primary sample only 14.7% of companies achieve exits. This is lower than the full sample as the primary sample only includes companies in the first round of financing (to control for passive stage drift), which carries more risk than later rounds.

I consequently construct the dummy variable *past performance* based on the VCF's prior exit rate. Many scholars in venture capital define the past exit rate based on the previous fund (for examples see Hochberg et al., 2007; Kaplan and Schoar, 2005). However, in my sample there are a lot of VCFs which establish multiple funds within a very short time span, for instance funds within the same year. This means that if the first fund is in the investment stage, the VCF's second fund is highly likely to be in the investment stage as well. Therefore, taking the first fund as a lagged performance to the second fund can in fact lead to a proxy of performance at the same time, or even future time if the first fund exits investments later than the second fund. Hochberg et al. (2007) use IPOs and M&A exits as a measure for lagged performance, but do not state if they do they exclude future exits, or how they deal with the fact that many funds are situated close in time to each other. Kaplan and Schoar (2005), explicitly look at performance persistence, a variable of interest in this paper as well. They use internal rate of return (IRR) and public market equivalent (PME) measures. PME measures the fund inflows and outflow in cash flow compared to what happens to the stock market. They take multiple lags, but again do not discuss the limited time gap between funds. Buzzacchi et al. (2015) measure the past performance by means of IRR data. They use the amount of write offs, which are defined as when the IRR= -1, over the total number of previous investments until the investment date. However, this measure still takes into account the future

[6] As Nahata (2008) also does, I match based on company name, since the VentureXpert database does not include identifiers. I take out all incorporation codes at the end, such as PLC and Inc. However, when matching on name there are some companies which have the similar names. To make the M&A exits more accurate I also match on the geographic state the VC fund is located in. This results in more accurate M&A exits, and is based on the assumption the company does not move to a new state between the financing and the M&A deal. In addition, there are multiple M&A deals done per company. I only look at those where there is a change in ownership, namely deals after which a new owner owns 50% or more of the shares. Furthermore, since companies can switch ownership multiple times after they receive venture financing, I look at the closest possible M&A date to the financing. Additionally, to increase accuracy for IPO deals, I also take out incorporation codes while matching, and moreover only look at the first IPO date of a particular company. In specific, companies which have multiple IPO dates have gone public, private and back to public again. Since these kind of companies are not in the venture stage after the IPO when they are private, they are excluded.

[7] The SDC IPO and SDC M&A database only record transactions above 100 million dollars. A smaller VC fund exiting via lot of M&A deals for less than 100 million would thus be recorded as having a worse performance than is the case. Therefore, there could be a small bias in this and many other research papers towards bigger VC funds. The variable *fund size* is examined in the data.

data of investments, as when analyzing a specific investment, the prior investments are not all exited at that moment in time.

I proceed as follows. First, since I do not have IRR or PME data, I measure a successful investment as in Hochberg et al. (2007) by means of an IPO or M&A deal. Second, to deal with the issue of using future data, I base the lagged performance measure on all the IPO and M&A *exits* which are completed before the company investment date, not the investments such as in Buzzacchi et al. (2015). In contrast to Buzzacchi et al. (2015), I do not have data on 'failed investments', only investments with a successful exit, and accordingly I construct an 'artificial exit date' to get the total number of investments made which could have been exited. I take an average of the time-to-exit for the sample and add this to the investment date of these non-exited companies. This takes into consideration exits which have 'failed' when they supposedly should have had an exit already based on the average time-to-exit.

4.2.3 Fund Inflows and Market Condition Variables

I) Fund Inflows

Fund inflows are a proxy of competition in the VC field (Hochberg 2007; Nahata, 2008). Hochberg et al. (2007) state that competition for deal flow affects can affect the quality of a VC fund's investments and correct for possible effects in addition to market opportunities as measured by public P/E and B/M ratios. Gompers and Lerner (2000) argue that VC industry inflows increase competition for a limited number of attractive investment options, which in turn increases the prices of these investment options. The more fund inflows there are, all other things being equal the more competitive the market is. Nanda and Rhodes-Kropf (2013) also look at competition for deal flow and demonstrate that supply of capital in the VC industry can lead to risk shifting. To address this, I retrieve the yearly number of dollars raised for VCFs located in the U.S. from the SDC Funding Database *(VC inflows)*.

II) Market Conditions

As stated above, venture investments are undertaken in private not public corporations, and so there are no easily accessible financial ratios. Previous research has taken this problem into account by examining public market multiples as a proxy for the market conditions in private markets (Gompers and Lerner 2000; Hochberg et al., 2007). Therefore, I construct two measures from the public markets which proxy for the price-earnings ratio *(Mean P/E)* and book-to-market ratio (*Mean B/M)* in the different industries respectively. To construct this measure I divide all COMPUSTAT companies into the six VentureXpert industries. First, I look at the companies that VentureXpert marks as haven gone public, and take the SIC codes from those companies.[8] Subsequently, I put the companies into a VentureXpert industry based on which industry the company's SIC code is most often matched to. I compute the P/E and B/M ratio in year *t* as the average of all the public traded companies in COMPUSTAT in those particular SIC codes in line with Hochberg et al. (2007).[9]

Additionally, I look at a number of other specifications in the robustness tests. Cumming et al. (2009) look at changing market conditions and the propensity to stage drift. They proxy market conditions by the change in returns of the Nasdaq composite index between the time of the fund founding date and the time of the investment. Accordingly, I construct *% increase Nasdaq* which proxies for a changing investment environment during the investment period (usually the first years) of the fund. Data is retrieved from Thomson Reuters Datastream.[10] Furthermore, Buzzacchi et al. (2015) look at changing market conditions by splitting their sample into bull and bear years, which in my data is examined with the variable *=1 if bull market*, defined as *all* calendar years in which the Nasdaq composite index is higher at the end of the year than at the start.

However, the variable for the bull market measured by Buzzacchi et al. (2015) is *only* defined for the years during the dotcom bubble of 1998 to 2000 inclusive, whereas the bear years are defined as all the other years in their sample the period 1998 to 2007. Similarly, Cumming et al. (2009) also include a dummy variable for the dotcom bubble. Consequently, I include a dummy for the dotcom bubble in my model (*=1 if during the dotcom bubble*). As my sample is also during the financial crisis, I also include a dummy for the U.S. subprime mortgage crisis in the model as well (*=1 if during the subprime mortgage crisis*).

III) Past Performance

In accordance with Kempf and Ruenzi (2008) and Buzzacchi et al. (2015), it could be that past underperformers and past outperformers alter their behavior according to different market conditions. Both Kempf and Ruenzi (2008) and Buzzacchi et al. (2015) take public market measures. However, as stated before the public market in which mutual funds operate is different from private markets. Increases in the public markets do not necessarily correspond to increasing funds into venture capital. Therefore, I directly measure fund inflows. I therefore include the interaction term *'past performance' * '% ln VC inflows'*, which captures how previously better and worse funds behave when the market changes.

[8] SIC codes in the VentureXpert database from public companies are taken from public corporation filings. Although there are also SIC codes for companies which have not gone public, these are less reliable. I consequently only use the SIC codes of those companies having gone public.
[9] In accordance with Hochberg et al. (2007) I winsorize the bottom and top 5 percentiles for both the P/E and B/M for each year. To make a value-weighted average I weight the market value of all companies in the COMPUSTAT database, and further assign a weight to a particular SIC code by the total dollar investment made each year by the VC funds in that respective SIC code. Moreover, in order to take the appeal of a sector as a whole for a VC fund into account, I do not correct for companies with negative earnings or book value on the fund level, in line with Gompers and Lerner (2000).
[10] In the case of weekend days, I use the closing price of the Friday before.

As an additional robustness tests however, measures similar to those used by Kempf and Ruenzi (2008) and Buzzacchi et al. (2015) are included, namely *'past performance' * '=1 if bull market', 'past performance' * '=1 if during the dotcom bubble', 'past performance' * '% increase Nasdaq', 'past performance' * 'Mean B/M' and 'past performance' * 'Mean P/E'*.

4.2.4 Drift Measures

For the different stages of development, I use the three VentureXpert definitions of early-stage, expansion-stage and later-stage, which strongly match those used by practitioners and VC trade associations such as the NCVA. In accordance with Cumming et al. (2009) and Buzzacchi et al. (2015) I map out the drift measure based on stage.[11] According to Buzzacchi et al. (2015), upward drifts and downward drifts can be viewed separately as shifting into more and less risk. Therefore, as upward and downward drifts might be fundamentally different, I follow this approach. *Downward drift* is defined as a dummy which is equal to one if the funds stage drifts downward, for instance a fund with a later stage focus investing in an early stage investment. *Upward drift* is defined as a dummy which is equal to one if the fund stage drifts upward in terms of the stage it invests in, such as a fund with a seed stage focus investing in an early stage portfolio company. Both variables are equal to zero if the fund investments are consistent with its focus, which is the case if for example a seed stage focused fund invests in a seed stage venture.

4.2.5 Persistence

It can be that there is persistence in drifting, namely that VCFs that have undergone stage drift in the past are more prone to drift in the future as well. To account for the potential that the measures used may capture the unobserved effect of omitted persistence in drift, I include the *lagged upward drift rate* and the *lagged downward drift rate* of the investments in the previous ten years before the current investment. It is sensible to limit the time of consideration for past drifts before a given investment date, as markets are changeable. The time period for the lagged variables is therefore equated to ten years, the average lifespan of a fund (Lerner, 1994),[12] and I measure the total investments done ten years prior to the investment date until one day prior to the investment date. I build the total number of drifts in either direction and normalize it by the total number of investments the fund made. The variables *lagged upward drift rate* and *lagged downward drift rate* thus measure the drift rate for a VCF as a percentage relative to investments made. Consistent with the rationale of the *past performance* variable, I measure

[11] Currently it is not possible to measure other forms of drift, such as industry or geographic drift in VentureXpert. According to Cumming et al. (2009), stage drift is the drift investors focus on, and is of much more relevance than industry and geographic drift.
[12] Results are robust for a 5-year and 15-year time span.

the past drift rate on the investment level before the investment date of the current investment, and do not take the drift rate of the previous fund for both constructs, as this could capture future returns.

4.2.6 Network Methodology and External Resource Access Measures

Network analysis has been used by many different researchers in different fields (Bonacich, 1987; Guler and Guillén, 2010; Hochberg et al., 2007). Network analysis is used to map out relationships between various actors in a network. In the case of venture capital, network analysis can be applied to syndication relationships. Figure 1 shows a graph of the syndication network of VCFs from 1993 – 1997, with nodes being the different players and arrows representing a syndication relationship. Influence can be measured by centrality, which is how central a node is in a network relative to other nodes.

In graph theory, an adjacency matrix can characterize a network. In this research I code two VCFs who invest in the same company as having a tie. I can capture these ties and measure the network by adjacency matrices, which can be directed and undirected. In a directed relationship it matters whether a VCF is a lead or co-investor, and in an undirected relationship it does not.

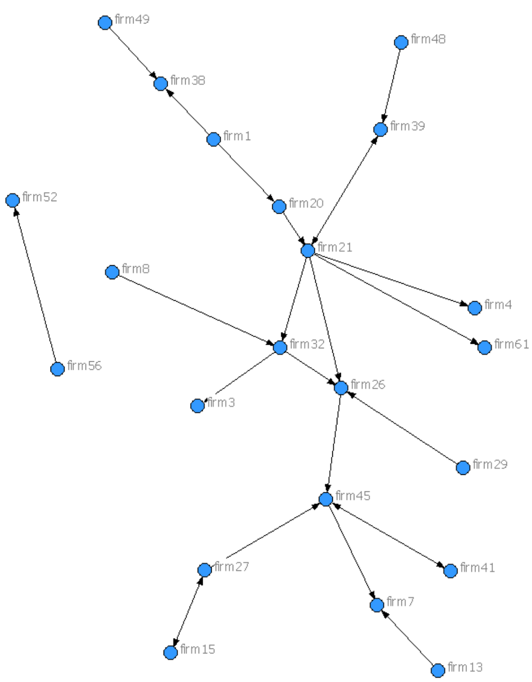

Figure 1: Network of Internet VCFs from 1993 until 1997

The figure shows the network of Internet VCFs which arises from the syndication of portfolio company investments during 1993 to 1997, the five years before the focal outbreak of the dotcom bubble. For ease of view, VCFs with no syndication relationships to others are excluded. Nodes in the graph represent VCFs and the arrow represent syndication ties. Arrows show the nature of the relationship, where an arrow points from the leading VCF to the non-lead member. An arrow in two directions displays that both VCFs led an investment with the other as non-lead member at some point in the same five-year time window.

A network can change over time, with different players coming into and exiting the network and affecting each VCF's centrality. Yearly networks are mapped out on the VCF level for each year *t*, and I measure the network on trailing 5-year windows in separate yearly adjacency matrices, in accordance with Hochberg et al. (2008).[13] I then use these matrices to calculate the five different centrality measures. I construct five centrality measures based on three conventional centrality measures.

I) Degree Centrality

In undirected data, *degree* measures the number of unique relationships a VCF has. The more relationships, the more opportunities there are for the exchange of information and resources, and thus the more centrally located the VCF is in the network. VCFs which have a higher degree of centrality can have an advantage, since they are less dependent on one relationship for access to information or deals and have a wider net from which they can retrieve knowledge, connections and capital. The *degree* measure goes from 0 (for VCFs that do not have any connections) to 1 (for VCFs with connections to all other VCFs in the network). The *degree* score for VCF *i* in year *t* is as follows:

$$degree_i = \Sigma_j p_{ij}/(n-1)$$

where p_{ij} is equal to 1 if a syndication relationship exists between VCF *i* another VCF *j*, and $\Sigma_j p_{ij}$ catches the total amount of syndicates a VCF has undergone. I divide by *(n-1)*, the total number of relationships possible in the network, to control for a fluctuating amount of total relationships possible, as different time windows have different amounts of VCFs active.

In directed data, there are two additional measures of degree. *Indegree* measures the amount of times a VCF co-invests with another VCF, therefore increasing its set of investment possibilities and also resources. The *indegree* score goes from 0 (for VCFs that failed to have a non-lead role in any syndicate) to 1 (for VCFs that achieved a non-lead role with every other VCF). The *indegree* score for VCF *i* in year *t* is as follows:

$$indegree_i = \Sigma_j q_{ji}/(n-1)$$

where q_{ji} is the number of co-investments which VCF *i* makes in other VCFs *j*, which is again normalized by dividing with *(n-1)*.

Outdegree measures the ability of a VCF to receive future investment opportunities from others it invites into its syndicates, by means of reciprocity. It counts the total number of other VCFs it has invited in its syndicates. The *outdegree* score goes from 0 (for VCFs that did not have a lead role in any

[13] In line with Hochberg et al. (2007), I do not I do not attribute different weights to investments which came earlier or later in a time window.

syndicate) to 1 (for VCFs that had a lead role in syndicates with all other VCFs). The *outdegree* score for VCF *i* in year *t* is as follows:

$$outdegree_i = \Sigma_j q_{ij}/(n-1)$$

where q_{ji} is the number of co-investments which VCF *i* makes in other VCFs *j*, again normalized by dividing with *(n-1)*.

II) Closeness

The closeness measure takes into account the quality of the relationships a VCF has. The measure I use is *eigenvector*, which looks at a VCF's network and weights how central the VCFs are which it is connected to. The *eigenvector* score goes from 0 (for VCFs that did not syndicate) to 1 (for VCFs that only syndicated with other central VCFs). *A* is the adjacency matrix for ties between *i* and *j*. The *eigenvector* score for VCF *i* in year *t* is as follows:

$$c_i = a\Sigma A_{ij} c_j$$
$$eigenvector_i = c_i/(max\{c_i\})$$

where *a* is the reciprocal of an eigenvalue, *A* is the adjacency matrix for ties between VCF *i* and *j*. The *eigenvector* for a VCF is sum of the eigenvector of all the other VCFs it is connected to. I normalize by dividing with the maximum possible eigenvector possible in a network of *n* actors.

III) Betweenness

Betweenness assigns a higher value to VCFs on whom many VCFs rely on to make connections in the network. A VCF with high *betweenness* stands in between many different actors. This gives that VCF the option to act as a broker and bring different VCFs without prior connection together. The *betweenness* score for VCF *i* in year *t* is as follows:

$$b_i = -\sum_j \left(p_{ij} \sum_q p_{iq} p_{qj} \right)^2$$
$$betweenness_i = b_i/(max\{b_i\})$$

where p_{ij} is the share of the network of *i* that is connected to *j* and p_{iq} is the share of the network of *i* that is connected to *q*, and p_{qj} is the share of the network of *q* that is connected to *j*, with $i \neq j \neq q$. I normalize by dividing with the maximum possible betweenness possible in a network of *n* actors.

4.3 Models and Assumptions

4.3.1 Models

To test the hypotheses, the following logit model is used for downward drifts.

$$Downward\ stage\ drift_i = \beta_0 + \beta_1(network\ measure_i) + \beta_2(past\ performance_i) + \beta_4(fund\ inflows_i) + \beta_5(past\ performance_i * fund\ inflows_i) + \beta_6(control\ variables_i) + \beta_7(company\ industry'_i) + \beta_8(fund\ stage'_i) + \varepsilon_i$$

In addition, the following logit model is used for upward drifts.

$$Upward\ stage\ drift_i = \beta_0 + \beta_1(network\ measure_i) + \beta_2(past\ performance_i) + \beta_4(fund\ inflows_i) + \beta_5(past\ performance_i * fund\ inflows_i) + \beta_6(control\ variables_i) + \beta_7(company\ industry'_i) + \beta_8(fund\ stage'_i) + \varepsilon_i$$

4.3.2 Assumptions

To use a logit model a number of assumptions need to be met (Wooldridge, 2009), these are: the data is not driven by outliers, enough cases per independent variable, no multicollinearity, independence of the error term, and linearity. In order to meet these assumptions, the below procedures are used.

First, to account for extreme values, all continuous values are winsorized at the 1% level. Second, as required by logistic regression, there need to be over 10 cases per independent variable (Peduzzi, 1996), which is the case. Third, there needs to be independence of the error term such that each observation is independent from each other. Even though the data is not in a panel setting, the data is limited to only first rounds, so there is no connection across time, and observations do not have a direct link with one another. The fourth requirement is the linearity assumption. The linearity of the continuous variables with respect to the logit of the dependent variable is reviewed with the Box-Tidwell procedure (Box and Tidwell, 1962). Using this procedure possible non-linearity of the independent variables with respect to the dependent variable is considered, and consequently a log transformation is applied when appropriate, which is the case for the *amount of investment by the syndicate*, the amount of yearly *fund inflows*, and the *experience invested dollars* and *experience companies* variables. Fifth, all variables are checked with the variance inflation factors (Wooldridge, 2009), and the VIF (variance inflation factor) score for all is below three. In the case of interaction terms, mean centering (Wooldridge, 2009) is used to remove issues regarding multicollinearity**.** Finally, heteroscedasticity is also corrected for using White standard errors (White, 1980) and by using a Huber Sandwich Estimator (McCullagh and Nelder, 1989).

5. RESULTS

5.1 External Resource Access Measures

5.1.1 Results

Table 4 shows the downward drift specification. The models (1) to (5) in this table each have a different external access to resources measure, used to test H1. All measures are positively significant at the 1% level. The *eigenvector* measure has the strongest effect with a one standard deviation increase associated with an increase in the likelihood of downward drifting of 21.3%. For the measures *degree*, *outdegree* and *indegree*, the same approach yields an increase in the probability of downward drift of 19.7%, 17.2% and 18.7%, respectively. Finally, *betweenness* is found to have the least economic significance, with a one standard deviation increase only leading to a 14.4% increase in the probability of downward drift.

Eigenvector scores higher than the other resource access variables. VCFs that have a high *eigenvector* are closer to all other actors in the network. Being closer to multiple actors means having closer access to their resources. The strength of this variable in the sample, also in relation with *degree*, *outdegree* and *indegree*, indicates that not only the quantity of syndicate relationships matters, but also the quality of these relationships in terms of leading to access to resources.

In contrast, *betweenness* scores lower than the other resource access measures. *Betweenness* is a measure of 'brokerage', the ability to connect different VCFs. It thus captures indirect relationships. In Table 4 this measure is less significant than the other measures, and the model also has a poorer fit, as measured by the Pseudo R2. Therefore, it shows that when downward drifting, indirect relationships are less useful to access external resources as compared to direct relationships. It should be noted that *betweenness* is also the variable of least economic significance in the paper of Hochberg et al. (2007), who study its effect on performance.

In contrast to the positive effect of resource access measures on downward drift in Table 4, where all measures are significant and positive, in the upward drift models in Table 5 the resource access measures are generally insignificant and negative. Only the *indegree* measure is found to be significant at the 5% level, with a one standard deviation increase leading into a 6.0% decline in the likelihood of drifting.[14] This shows that VCFs that get invited into more deals by other VCFs actually tend to upward drift less.

[14] The regressions in Table 4 and Table 5 have a different amount of variables as later stage VC funds can not upward drift and seed stage VC funds can not downward drift, and are excluded in the upward drift and downward drift equations, respectively. The different amount of variables in Table 4 and Table 5 is highly likely to be the case that in Buzzacchi et al. (2015) as well, but in their tables the authors only report the number of observations for downward drift and exclude those for upward drift.

Table 4:
Effect of Resource Access on Downward Stage Drift

The dependent variable in this table is *downward stage drift*, which has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: c*ompany age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged downward drift rate* is the downward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
Company and investment characteristics					
Company age	-0.570***	-0.570***	-0.569***	-0.567***	-0.575***
	(0.0508)	(0.0509)	(0.0507)	(0.0507)	(0.0510)
ln amount invested by syndicate	-0.348***	-0.348***	-0.344***	-0.352***	-0.340***
	(0.0253)	(0.0252)	(0.0252)	(0.0253)	(0.0251)
Number of VC funds in syndicate	0.0307**	0.0330**	0.0302**	0.0306**	0.0322**
	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)
=1 if company from California	0.206***	0.219***	0.202***	0.192***	0.234***
	(0.0660)	(0.0658)	(0.0661)	(0.0662)	(0.0658)
=1 if company from Massachusetts	0.282***	0.286***	0.279***	0.274***	0.290***
	(0.0953)	(0.0952)	(0.0954)	(0.0953)	(0.0953)
=1 if lead VC fund	0.0515	0.0510	0.0579	0.0525	0.0526
	(0.0882)	(0.0883)	(0.0882)	(0.0884)	(0.0882)
VC fund and VCF characteristics					
=1 if first fund	0.164*	0.156*	0.157*	0.177**	0.156*
	(0.0893)	(0.0891)	(0.0893)	(0.0896)	(0.0891)
Fund sequence	-0.0101	-0.0100	-0.00867	-0.0118	-0.00303
	(0.00972)	(0.00969)	(0.00955)	(0.00987)	(0.00926)
Past performance	-0.0933	-0.0962	-0.0699	-0.119	-0.110
	(0.125)	(0.124)	(0.125)	(0.125)	(0.124)
Fund inflows and market conditions					
=1 if during the dotcom bubble	0.000929	0.0184	-0.00597	-0.0155	-0.00933
	(0.0872)	(0.0871)	(0.0871)	(0.0875)	(0.0873)
=1 if during the subprime mortgage crisis	0.399***	0.387***	0.399***	0.395***	0.400***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
ln VC inflows	-0.0603	-0.0849**	-0.0675*	-0.0787**	-0.0849**
	(0.0376)	(0.0362)	(0.0370)	(0.0364)	(0.0364)
Mean P/E	-0.00900**	-0.00889**	-0.00909**	-0.00932**	-0.00933**
	(0.00368)	(0.00368)	(0.00367)	(0.00367)	(0.00367)
'Past performance' * 'ln VC inflows'	0.0335	0.0288	0.0158	0.0828	0.0858
	(0.0845)	(0.0843)	(0.0846)	(0.0848)	(0.0848)

(continued)

Table 4 - *Continued*

	(1)	(2)	(3)	(4)	(5)
Persistence					
Lagged downward drift rate	0.984***	0.988***	0.965***	0.981***	1.029***
	(0.133)	(0.132)	(0.133)	(0.133)	(0.132)
Resource access measures					
Degree	0.0588***				
	(0.0114)				
Outdegree		0.0331***			
		(0.00646)			
Indegree			0.0534***		
			(0.0102)		
Eigenvector				0.0319***	
				(0.00611)	
Betweenness					0.179***
					(0.0403)
Intercept					
Constant	0.0323	0.183	0.0835	0.113	0.200
	(0.244)	(0.238)	(0.242)	(0.240)	(0.237)
Diagnostics					
Observations	6,432	6,432	6,432	6,432	6,432
Pseudo R-squared	0.165	0.165	0.165	0.165	0.164
Log likelihood	-3410	-3410	-3409	-3409	-3413

Table 5:

Effect of Resource Access on Upward Stage Drift

The dependent variable in this table is *upward stage drift*, which is equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged upward drift rate* is the upward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
Company and investment characteristics					
Company age	0.677***	0.676***	0.676***	0.676***	0.678***
	(0.0484)	(0.0484)	(0.0483)	(0.0484)	(0.0484)

(continued)

Table 5 - *Continued*

	(1)	(2)	(3)	(4)	(5)
ln amount invested by syndicate	0.310***	0.311***	0.311***	0.313***	0.307***
	(0.0367)	(0.0367)	(0.0367)	(0.0369)	(0.0365)
Number of VC funds in syndicate	0.0101	0.00983	0.0120	0.0100	0.00870
	(0.0187)	(0.0187)	(0.0188)	(0.0187)	(0.0186)
=1 if company from California	-0.288***	-0.290***	-0.280***	-0.283***	-0.296***
	(0.0811)	(0.0809)	(0.0813)	(0.0814)	(0.0808)
=1 if company from Massachusetts	-0.248**	-0.249**	-0.246**	-0.245*	-0.247**
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
=1 if lead VC fund	0.0891	0.0891	0.0846	0.0873	0.0922
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
VC fund and VCF characteristics					
=1 if first fund	-0.163	-0.161	-0.162	-0.168	-0.158
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
Fund sequence	-0.0102	-0.00805	-0.00491	-0.00847	-0.0159
	(0.0128)	(0.0128)	(0.0126)	(0.0130)	(0.0123)
Past performance	0.223	0.223	0.207	0.229	0.225
	(0.152)	(0.152)	(0.152)	(0.152)	(0.153)
Fund inflows and market conditions					
=1 if during the dotcom bubble	-0.174	-0.176	-0.157	-0.167	-0.183
	(0.114)	(0.113)	(0.114)	(0.114)	(0.114)
=1 if during the subprime mortgage crisis	-0.0699	-0.0624	-0.0637	-0.0683	-0.0759
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
ln VC inflows	0.0373	0.0398	0.0221	0.0396	0.0546
	(0.0455)	(0.0439)	(0.0454)	(0.0445)	(0.0445)
Mean P/E	0.000551	0.000482	0.000648	0.000693	0.000494
	(0.00465)	(0.00465)	(0.00467)	(0.00466)	(0.00464)
'Past performance' * 'ln VC inflows'	-0.379***	-0.374***	-0.373***	-0.396***	-0.382***
	(0.105)	(0.105)	(0.105)	(0.106)	(0.105)
Persistence					
Lagged upward drift rate	0.815***	0.807***	0.782***	0.809***	0.834***
	(0.182)	(0.182)	(0.181)	(0.182)	(0.182)
Resource access measures					
Degree	-0.0177				
	(0.0146)				
Outdegree		-0.0131			
		(0.00843)			
Indegree			-0.0300**		
			(0.0140)		
Eigenvector				-0.0107	
				(0.00781)	
Betweenness					-0.0171
					(0.0518)
Intercept					
Constant	-3.150***	-3.169***	-3.075***	-3.158***	-3.242***
	(0.308)	(0.302)	(0.306)	(0.306)	(0.302)
Diagnostics					
Observations	5,781	5,781	5,781	5,781	5,781
Pseudo R-squared	0.220	0.220	0.221	0.220	0.220
Log likelihood	-2409	-2409	-2407	-2409	-2410

This provides evidence against H1 (VCFs with a higher access to external resources downward drift more).

To sum up, the different resource access measures confirm hypothesis 1 for downward drift, but present contrasting evidence for upward drift. Downward drifting due to the network is much more attractive if the risk-return characteristics of investments can be considerably improved due to the usage of partner VCFs' resources. A positive significant coefficient for the resource access measures indicates that partner resources indeed improve the risk-return characteristics, and VC funds downward drift. For upward drift however, a negative coefficient is found, and in the next section this is looked into in depth and possible explanations of these findings are discussed.

5.1.2 Possible Explanations of Results

For downward drifts, VCF's with increased access to resources downward drift more, in line with hypothesis 1. On the other hand, some evidence has been found of the opposite effect for upward drifts, namely that VC funds with increased access to resources upward drift less. Therefore, I explore four speculative theories that are compatible with these findings below.

I) Active versus Passive Drift

In the sample only active drift is examined and passive drift is ignored, as only first rounds are studied (similar to Cumming et al., 2009).[15] Passive drift can be explained as follows: if an investment made by a VC fund was consistent with its stage focus, but the portfolio company grows into a higher stage of development, and the VC fund chooses to invest again, this time it invests outside its stated stage focus, therefore drifting in a passive manner.

An explanation of the contrasting results for hypothesis 1, regarding upward and downward drifts, is that VC funds need partners to downward drift, but can perform upward drifts themselves by passively drifting. This explanation can be broken down into two different theories. The first is that VC funds do not need to have access to external resources to upward drift, as they invest only in their own portfolio companies. As can be seen from Table 6, which looks at active and passive drift, this argument is not valid, as VC funds still perform 40.3% of upward drifts into companies which they have not invested in before, showing there could still be the need for resources from others to upward drift. The second theory is that VC funds do not need to rely on external resources, because of their experience from previous investments in portfolio companies which have grown into higher stage. Still, this only covers treatment

[15] Table 6 shows that active downward drift is predominantly done in the first round. Active downward drift has been compared for the first rounds to non-first rounds, but findings remain the same.

resources and not selection resources. Particularly, when performing upward drifts into its portfolio companies that have grown to a higher stage, the VC fund does not actively pick companies to upward drift into and therefore it is highly likely it still lacks the selection resources necessary to invest in this specific stage.

Table 6:

Active and Passive Stage Drift

This table presents the occurrence (and corresponding percentages) of both upward and downward stage drifts for VC funds for the period 1980 – 2010. *Upward drift* excludes funds with a focus on later stage investments, while *downward drift* excludes funds with a focus on seed investments. *No drift* means that the VC fund did not drift and invested consistent with its stage focus. The column first round is the same as the sample used in Table 4 and Table 5 and only includes first round investments. In contrast, 'active and passive drift' includes investments from all rounds. The columns 'only active drift' and 'only passive drift' are both subsets of the proceeding column.

		First round	Active and passive drift	Only active drift	Only passive drift
Drift type	Upward drift	2,645	22,229	8,958	13,271
		(20.40%)	(49.59 %)	(40.30%)	(59.70%)
	Downward drift	3,881	6,022	4,956	1,066
		(29.93%)	(13.44%)	(82.30%)	(17.70%)
	No drift	6,442	16,572		
		(49.68%)	(36.97%)		
	Total	12,968	44,823		
		(100%)	(100%)		

II) Capital Trades for Resources

Hochberg et al. (2015) find evidence that suggests that tie formation between two VCFs is especially beneficial when one is endowed with high levels of experience, resource access, and breadth of investments (measured across industry, geography and scope) while the other has low levels of experience, resource access and breadth of investments, but high levels of available capital, which they call 'high value-added' pairing with 'dumb money'. In their work 'available capital' is a construct of multiple variables, and is captured mainly by the assets under management, the dollar volume of investment, and the uninvested capital of a VCF.

Since the VC funds in my sample are all focused on a specific stage, it is highly likely that they have inferior treatment and selection resources relative to VC funds that are more familiar with those stages. In line with expectations, sample VCFs with a style focus on later stages invest larger sums are of money per investment round. I therefore hypothesize that funds focused on those stages also have a larger fund size and thus more 'available capital'. If this hypothesis holds, it would explain the contrasting results for upward and downward drift. In specific, funds from a higher stage have more capital, and when downward drifting they trade dumb money for resources when investing in a lower stage. On the contrary, when VC funds from lower stages of development upward drift, they have less capital and also do not have the resources available for investing in that stage. To test the hypothesis, that high-value added indeed trades with resources, I look at the median fund size in the sample. The sample uses the same database as Hochberg et al. (2015) and the median fund size can be seen as proxy for assets under management. Seed stage funds ($18.0m) have a significantly lower median fund size compared to early ($68.0m) and later stage funds ($67.8m). Nevertheless, the latter two have approximately equal fund size, which is contrary to expectations, as the hypothesis expects that later stage funds have a larger fund size than early stage funds. This indicates that *either* the median fund size *incorrectly proxies* for available capital in the database, and the hypothesis could still hold true, *or* if the fund *correctly proxies* for available capital, it indicates that dumb money trading for resources is not the reason for the contrasting results of upward and downward drift.

III) Staging of Investments

Sahlman (1990) shows that staging can create option-like returns for a VC fund, and that VC funds first invest a small amount in order to 'have a chair at the table' to be in a good position compared to other VC funds to potentially commit more capital in a later round. The staging of investments thus has two benefits. First, it increases the option-like characteristics of an investment by having more financing rounds relative to a VC fund's own stage. Second, VC funds position themselves well if the company reaches their own stage of development and are then able to use its own resources. By upward drifting however, VC funds decrease the option-like characteristics of the investment, and consequently they cannot invest in the company when it reaches their stage, as an upward drift is in a higher stage of development. This severely limits the possible impact that their own resources can have on the investment. Taken together, a decreasing option value of an investment relative to their committed stage focus, and the inability to use their own resources at some point later in time, can lead VC funds to have a strong preference for downward drift as compared to upward drift when presented with options from within their network.

IV) Information Asymmetry

Information asymmetry has been found to be higher for companies in earlier stages (Gompers, 1995; Trester, 1998). If this is true, there can be more uncertainty and consequently more mispricing in earlier stages. Therefore, a network could lead to more 'golden opportunities', where a VC fund's syndicate partners are able to use their resources to find investments with attractive risk-return characteristics, and the VC fund joins in on the investment opportunity. In contrast, much more is known regarding later stage companies, due to an often bigger size and longer operating history. If information asymmetry in these stages is lower, the misalignment of risk-return is also likely to be less common, and good opportunities are harder to find. This would explain the positive coefficient of the resource access measures in Table 4 and the negative resource access measures in Table 5, as external resource access in this case would predominantly lead to more opportunities in lower stages.

As stated before, these four theories are highly speculative alternative reasons, and would need to be examined in further detail before any firm conclusions can be drawn.

5.2 Past Performance

Previous research has shown that better performing funds take on less risk in comparison to those with poor past performance due to fund inflow incentives, and poor past performers take on more risk in comparison to better past performers due to termination risk (Buzzacchi et al., 2015; Brown et al., 1996; Schwarz, 2013). The past performance variable is not found to have significance in Table 4 or Table 5. VCFs with better performance having a negative coefficient for downward drift and a positive one for upward drift, showing some consistency with the theory that better performing funds drift less and poorer performing funds drift more. Nonetheless, it is not possible to accept hypothesis 2.

5.3 Past Performance under Changing Fund Inflows

The *'past performance'* * *'fund inflows'* is negatively significant at the 1% level for upward drifts in Table 5. This shows that better performing funds are less likely to increase risk when fund inflows are higher (and therefore also competition among funds is fiercer; see Hochberg et al., 2007), and confirms hypothesis 3 for upward drift. In Table 4 no effects are found for downward drift.

Termination risk is the risk of a fund manager losing his job due to bad performance. Termination risk is a stronger incentive when there is less money available in the VC industry, as LPs scrutinize their investments more, and if a poor past performing fund manager does not improve performance, there is a higher likelihood that he is fired (Kempf and Ruenzi, 2008; Buzzacchi et al., 2015). The results in Table 5 are consistent with this theory and indicate that poorly performing funds 'play it less safe' by upward drifting less in times when there is less funding. This suggests that when there is less money to go around and LPs increasingly inspect whom to hand their money, poorly performing fund managers increase their risk in order to hold on to their job.

Fund inflow incentives motivate a fund manager to increase risk in order to receive more funding from LPs. Since a fund's performance is relative to others, an increase in a fund's performance that places it amongst the top performing funds can attract a sustainably larger amount of inflows. When there is more funding available, this effect is stronger (Kempf and Ruenzi, 2008). The results in Table 5 are consistent with this explanation and show when there is more money to go around, better performing funds are less likely to 'play it safe', by limiting the amount of upward drifts. Better performing VC funds thus seem more eager to take on risk in times of high inflows, in order to exhibit higher performance than competitors, in order to attract a disproportionate amount of fund inflows.

The results are consistent with fund inflow incentives and termination risk explanations as of Kempf and Ruenzi (2008) as well as Buzzacchi et al. (2015), the latter who also only find significance in the upward drift specifications. Additionally, although Nanda Rhodes-Kropf (2013) do not take stage drift into account, the results show some compatibility, as during periods with more fund inflows - a possible proxy for past performance - more experienced VCFs invest in riskier and more novel startups

5.4 Market Conditions

The *mean P/E* variable is negatively significant for downward drifts. The economic significance of a one standard deviation decrease in the *mean P/E* variable increases the likelihood of drift by 7.2 - 8.2% across the different specifications in Table 4. The variable *mean P/E* captures the yearly P/E across different industries. This indicates that if the *mean P/E* decreases, there are more good investment opportunities in that sector. Table 4 shows this can lead to riskier behavior as VC funds are increasingly likely to downward drift.

Cumming et al. (2009) and Buzzachi et al. (2015), proxy better market opportunities with the general stock market, which is similar to price, or 'P', part of the P/E ratio in this research. They display that when the stock market goes up, drift increases. The *mean P/E* shows consistency with their market condition variables. However, to be sure this variable and my sample has consistency with theirs, in Table 14 and Table 15 of Appendix 6 I run a robustness test where I split the data into bull years, indeed showing consistency with previous research.

The *ln funding inflows variable* in Table 4 is positively significant at the 5% level for *outdegree*, *eigenvector* and *betweenness*. As the variable captures increased competition (Hochberg et al., 2007), it expected that when there are more fund inflows into the VC industry, VC funds are more active in the market, and accordingly there are fewer good opportunities available. Consequently, a VC fund should be more likely to stick to its stage focus. However, when taking into account the offsetting effect of the interaction term *'past performance' * 'ln funding inflows'*, the total effect of *ln funding inflows* becomes negligible.

5.5 Other Variables

The dummy variable for the first fund is found to be significantly negative at the 5% level for the eigenvector downward drift specification in Table 4, and is insignificant across other specifications.

Regarding the eigenvector specification, if the VC fund is a first time fund, the likelihood of drifting increases by 19.4%. This result directly contrasts the 'reputation hypothesis' of Cumming et al. (2009), who frate that VC funds with less experience drift less due to reputation costs. On the other hand, this supports the 'specialization hypothesis' of Wermers (2012), which states that funds build up certain expertise in a sector, creating economies-of-style specialization. Therefore, the results indicate that first time funds drift more, as they have less to lose from deviating from their specialized stage expertise. However, Cumming et al. (2009) report opposing findings. The findings are most likely different from Cumming et al. (2009) due to the inclusion of network variables, which can be seen from Table 12 and Table 13 in Appendix 5, where the first fund variable switches direction when excluding the resource access measures.

The *company age* and the *ln amount invested by the syndicate* are both negatively significant for downward drifts, and the reverse holds true for upward drifts. This logically makes sense as downward drifts, by default, are observed in companies in earlier stages. These types of companies are likely to be younger and smaller, and therefore in need of less funding. In contrast, upward drifts are more prevalent in companies in higher stages of development, thus more likely to have a higher company age, and be in need of a higher amount of funding.

For the dotcom bubble dummy, no effects are found. However, the dummy for the subprime mortgage crisis is significant, and increases the likelihood of downward drifting by 48 - 49% across all models in Table 4. For upward drifts no effect is found. These findings are consistent with the *mean P/E* variable. Specifically, during crisis times, valuations are generally lower. This shows that in (extreme) periods with lower valuations, as measured by the *mean P/E* and the subprime mortgage dummy, VC funds significantly take on more risk. Nevertheless, an alternative explanation of this effect could be that VC funds 'time' their investments to have favorable exit conditions (Lerner, 1994), as when economic conditions are poor, IPO and M&A markets are likely to be poor as well. Consequently, downward drifting lengthens the time it takes for a company to have an exit, possibly mitigating poor economic conditions.

5.6 Persistence and Causality

I do not believe my results are driven by reverse causality where a higher drift rate enables a VC fund to increase its access to external resources, instead of access to resources leading to higher drift, as I construct different measures of resource access from data for the five years *previous* to the first investment a fund makes.

However, it can be argued that funds that drift do not do so as a result of access to resources, but because they drifted in the past and are therefore more prone to drift in the future as well. To exclude this effect, the measures for resource access proxy for omitted persistence in drift the model by default include the lagged down(up)ward drift rate of the investments in the previous ten years before the current investment. The coefficients in Table 4 and Table 5 are very significantly positive, showing there is persistence in drift, and indicating that mean reversion effect of Schwarz (2013) is not at work here, but that funds that drift more in the past have a higher likelihood of drifting in the future.

Including the lagged down(up)ward drift rate reduces the observations to investments which could have had the possibility of an exit occurring, either by an actual investment, or by a non-exit the (the latter measured by adding the average time to exit of my sample to the non-exited investment). A model excluding the lagged down(up)ward drift rate is looked at in the robustness tests section, but does not lead to different conclusions.

5.7 Evaluation of Network as Proxy for External Resource Access

Scholars have argued that the roles of a VCF network can be resource access, but also risk sharing and reciprocity. Therefore, in the following section I look at scholars who have pointed to differing roles of the network other than resource access, and show that the network accurately proxies for resource access in the sample.

First, reciprocity is measured by inviting another VCF into your syndicates in hope of future deal flow from them (Locket and Wright, 2001; Manigart et al, 2006). *Indegree* captures the amount of times a VCF participates in other's deals, and this measure therefore by default excludes the option of reciprocity. Therefore, is highly unlikely reciprocity is a factor that affects the decision to drift.

Second, the risk sharing hypothesis states that a network is mostly used to share risk, which is stronger when the deal size is larger (Locket and Wright, 2001). Larger deal sizes require more capital, and when more capital is needed, VC funds do not want too much exposure and therefore want to share the investment with others. When VC funds downward drift, they do so into earlier stage of development, which have smaller deal values. When VC funds upward drift they do so into higher stages of development, which have larger deal sizes. In the sample for upward drifts, all specifications for the network measures are negative, with *indegree* being significantly negative, indicating that VC funds do not use the network to invest into larger deal sizes. In contrary, they seem to use the network to downward drift, and thus actually invest into smaller deal sizes. Consequently, it also is highly unlikely that the effect of resource access on drifting is due to risk sharing.

Since *indegree* largely rules out the option of reciprocity as well as risk sharing, it is highly likely it is a proxy for resource access. The other network measures show similar effects to *indegree*, so it is most probable that the network is indeed an accurate proxy for access to resources.

5.8 Robustness Tests

Several robustness tests have been run. First, it could be that the network actually proxies for a VCFs' reputation. Therefore, in Table 10 and Table 11 of Appendix 3, the reputation measure of Nahata (2008) is looked at. This *reputation* measure based on a VCF's cumulative IPO share is different from Buzzacchi et al. (2015), who measure reputation by management fees. Nevertheless, both Nahata (2008) and Buzzachi et al. (2015) state that their variables proxy for the reputation of a VCF. Accordingly, in model 6 of Table 10, *reputation* is found to have a large positive impact on downward drift. Although a VCF's *reputation* exhibits some tendencies of multicollinearity with the network, all network measures stay significantly positive. In addition, in Table 11 *reputation* is found to be insignificant with regards to upward drift. The results indicate that upward and downward drifting are really driven by a network, and do not merely capture unobserved effects of a VCF's reputation.

Second, as touched upon before, in all models I include the variable of the *lagged drift rate* by default to correct for persistence. In Table 12 and Table 13 of Appendix 4, the models have been run without this persistence variable. When examining downward drift in Table 12 the results become stronger and more significant. Namely, the *number of VC funds in syndicate*, the *first fund dummy* and the *ln VC inflows* become significant at the 1% level. Furthermore, all these variables and the network measures have a larger impact and thus show increased support for the findings presented in this research. When examining the upward drift in Table 13, the *past performance* variable becomes significant at the 10% level. The *ln VC inflows* becomes higher, and the network measures become stronger, with *indegree* significant at 1%. As was the case with Table 12, all variables again display increased support for the findings offered.

It could be that different experience measures can explain why VC funds downward drift more and upward drift less, instead of resource access. Many experience variables exhibit multicollinearity with resource access variables, and cannot be included into the model along with resource access. Hence, in Table 14 and Table 15 of Appendix 5, different experience variables are examined. All models considerably decline in Pseudo R2, and no significance is found for any experience variables, except for the variable *fund sequence* which has 10% significance in the downward drift Table 14. Comparing this with Table 4 where *fund sequence* is not significant shows that *fund sequence* in Cumming et al.'s (2009) research most likely captures the omitted variable of the network.

Since Cumming et al. (2009) and Buzzacchi et al. (2015) use public market data instead of fund inflows, I check their specifications to assess whether the data used here can be seen as consistent with theirs. The variable of the *% Nasdaq increase* of Cumming et al. (2009), as well as *'past performance' '% Nasdaq increase'* are not significant.

In the methodology used in Buzzacchi et al. (2015), the authors use bull and bear market years. However, in their work the years of the dotcom bubble are the only years considered as bull years and the rest of the years are considered to be bear years. The methodology used by Buzzacchi et al. (2015) is captured by the variable *'past performance'* * *'=1 if during the dotcom bubble'* in model 6 of Table 16 and Table 17 of Appendix 6, and is not significant. In contrast however, when specifying the bull and bear market years by a more conventional method, namely by labeling a year a bull year when the Nasdaq has gone up during the calendar year, and a bear year when the Nasdaq has gone down, I find significance for the coefficient *bull market* (and therefore also the reverse, *bear market*) at 5% for downward drifts in Table 16, showing bull years could lead to more stage drift due to market conditions (and bear years to less), consistent with Cumming et al. (2009) and Buzzacchi et al. (2015). Nonetheless, the interaction term of the *bull* and *'past performance'* * *'bull market'* variables in Table 16 and Table 17, as well as the *bull market* variable in Table 17 are not significant. Furthermore, in model (5) of Table 17, the interaction term of *'past performance'* * *'mean P/E'* becomes significant, but the overall model fit as measured by Pseudo R2 decreases as compared to model (3) of Table 5. In retrospect, these results show consistency with previous research, while at the same time showing validity for usage of different variables in Table 4 and Table 5, due to a significance levels and a higher model fit.

Finally, the sample is also split into individual fund stages and their likelihood of drifting upward or downward by one or multiple stages is examined. In comparison to Table 4 and Table 5 no differences in the direction of coefficients is found across models, yielding validity to a segmentation of the sample into upward and downward drifts.

6. CONCLUSION

In this research I construct a U.S. sample of 12,968 investments by 2,195 U.S.-based VC funds from 1980 until 2010 that commit to a certain style. With this data, upward and downward stage drifts are studied separately. I hypothesize that access to external resources leads VC funds to upward and downward drift more. It is found VC funds with increased access to external resources do in fact tend to downward drift more, but some evidence is found that they upward drift less. Four theories are presented as to why this could be the case. In addition, past performance is mapped out with a new methodology. Poorly past performing funds tend to be less keen on playing it safe by upward drifting in times when fund inflows are low, while better past performing funds tend to upward drift less in times when fund inflows are high, which is consistent with termination risk and fund inflow incentives, respectively. Finally, better (worse) market opportunities have been found to increase (decrease) the amount of risk a fund takes by downward drifting.

There is an ample quantity of research regarding mutual funds, but there is a significant gap in the venture capital literature on drift. Like Cumming et al. (2009) and Buzzacchi et al. (2015), this research has taken steps in closing that gap. The contribution to the current body of research is twofold. First, I hypothesize and show evidence for a novel theory that network resources are a significant factor in deciding if a stage drift is undertaken. Second, for the first time a U.S. venture capital sample has been examined, and evidence has been found that signals the existence of termination risk and fund inflow incentives, consistent with European research.

For practitioners, this research highlights a nuance in how LPs should view stage drift. Previous work has mostly found that stage drift signals agency costs and ‘fund manager inadequacy’, but also that market opportunities can lead a VC fund to drift. This research sheds new light on the rationale of stage drift and finds that stage drift occurs due to the valuable resources available via a network to a VC fund, thus showing that not all stage drifts are created equal. As different market conditions and a network can lead a VC fund to take on more or less risk, it can be that by stage drifting a VC fund actually maximizes its potential, by better applying knowledge about the market and its resource base, thus in fact signaling ‘fund manager adequacy’. Stage drifts which do not arise from termination risk and fund inflow incentives could therefore be beneficial to LP performance. At the same time however, stage drift could also could lead to potential diversification losses in the LP’s portfolio. Therefore, in order to advocate certain types of stage drift to be allowed in covenants, further research is needed.

6.1 Limitations

Firstly, the analysis done is on the investment level. It can also be argued to be done with panel data or on the fund level. This investment level approach is taken due to alignment with previous research as well as to isolate the effect of a network and to control for company level aspects. These company level aspects include market conditions, syndication characteristics of individual deals, and the amount of yearly fund inflows, all important variables which would have been lost in panel data on the fund level.

Secondly, I look at VC funds with a defined stage focus. However, this does not mean the fund’s parent has the same fund stage focus and stage resources. It could be that a fund’s parent has acquired a lot of resources in other stages from years of investing, or even that the funds parent currently has funds operating in different stages, which could impact the fund’s tendency to stage drift.

Thirdly, most data is on early stage VC funds, consistent with Cumming et al. (2009) and Buzzacchi et al. (2015). Therefore, most of the effects found in this, and previous, research mainly pertains to funds with an early stage focus.

Finally, I have not been able to control for covenants (see Gompers and Lerner 1996). Convents specify which actions a VC fund can take and which not. Stage drift is something done quite frequently in venture capital, with 50.3% of investments being drifts in my sample. It could be that upward drift is of less importance, as in my talks with industry experts they stated that the type of drift which is the main concern for LPs is downward drift, as by downward drifting VC funds to take on more risk, and by upward drifting they take less risk, and therefore upward drift is not interpreted negatively. Even so, a substantial amount of investments are downward drifts, namely 29.9% in my data, and 26.8% in the data of Buzzacchi et al. (2015). Since there seems to be a high amount of downward drift (as well as upward drift) this calls into question what the role of covenants are and if most of the stage drifts done are actually allowed and within the stated scope. Further work with surveys focusing on covenants between LPs and GPs would bring much more insight into this area.

6.2 Further Research

In combination with Cumming et al. (2009) and Buzzacchi et al. (2015), this paper provides the first steps into the analysis of stage drift in a private equity and venture capital setting. Due to the considerable gap on prior studies done on drift, there are many different avenues for future research that can be further investigated.

Firstly, the positive effect of resource access measures on downward drift, as well as its negative effect on upward drift can be further studied. The reason for this might lie in one, or a combination, of the four theories I put forward, and can be examined in further depth with empirical work.

Additionally, a network among VCFs could be specified differently. Firstly, the network can be reexamined by splitting it into upward drift networks and downward drift networks. Take for instance two VCFs with an early stage focus who both have the same network strength. However, if the first has a relatively larger network with VCFs who invest in seed companies, it is possible that the first downward drifts more to seed companies than the second, due to a higher network strength with VCFs *in that particular* stage. Upward drifts can be specified in a similar way. Secondly, the quality of ties can be taken into account. Remember that our network measures and those of Hochberg et al. (2007) do not take into account repeat investing. However, repeat investing is associated with an increased access to external resources (Hochberg et al., 2015; Sorenson and Stuart, 2001; Wright and Lockett, 2003). Again, visualize two VCFs who have the same network strength but of which the first has a network that consists of a lot of close partners, whereas the other invested with the same partners, but only once or infrequently. It is highly likely that the first VCF with stronger ties has increased access to its syndicate partners, as stronger ties between two VCFs can make it easier to gain access to treatment and selection resources of the other. In addition, a network could be specified differently than amongst VCFs. Other types of social networks such as linkages to portfolio companies, industry experts or influential (government) decision makers, can also be interesting to look at, and could also lead to an investment firm drifting.

Thirdly, style drift can be expanded to other investment firms. Outside of the venture capital scope, this research can be extended to a PE or even other investment firms setting. Relationships in venture capital are in general tighter than other types of investment firms. Regarding mutual funds however, Cohen et al. (2008) find that mutual fund managers place larger bets on management that is part of their social network created in university, and therefore outperform. It would be interesting to look if these, or other kinds of, social networks can lead investment firms to style drift in order to capture better opportunities coming from network resources.

Moreover, drift could be defined differently. The main database used in this research is VentureXpert, which only specifies a committed fund focus to a stage, not an industry or geography. Although literature has indirectly proven that access to resources via network partners can lead to more distant investing (Sorenson and Stuart, 2001), it has not proven that this could lead to style drift. It would be interesting to also look industry drifts or geography drifts with survey research, as these could have different effects.

Furthermore, contrarian investing and herding behavior can be also looked at. In line with Wermers (2012) herding behavior is another aspect that can be viewed in relation to VC stage drift. It could be that funds which upward or downward drift first, do so in higher quality companies than VC fund who follow them.

In addition, the performance of drifting has not been adequately studied. What should be taken into account here is not only the exit percentage, but also exit variance could be important. This might be a factor which plays case in the research of Nanda and Rhodes-Kropf (2013). Although their sample is limited seed and early stage companies, and they do not differentiate between VC funds with and without a stated fund focus, they do document that times of more funding can lead VC funds to invest differently. They find that VC funds invest in much more innovative companies, with a higher chance of bankruptcy, but which also have a higher chance of a larger exit.

Finally, the actual responses of venture capital LPs to GP style drift can be studied. From conversations with LPs, Ramsinghani (2011) notes that LPs do not reward performance coming from style drift. Is this really true? This can quite easily be investigated empirically by examining if LPs give more or less funding to a GP in a subsequent period in time. If LPs reward performance, style drifts with higher performance should lead to a bigger follow up fund for the VCF, all other things equal. On the other hand, if LPs feel style consistency is important, style drifts in general should lead to a smaller next-period fund.

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APPENDICES

Appendix 1

Table 7:
Correlation Matrix of Sample Variables

This table presents the correlation matrix of the sample of VC funds for the period 1980 – 2010. *Company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *VCF age* is measured as the amount of years between the first investment made by the fund and the first investment made by the fund's parent. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. *Fund size* is the amount of capital committed reported in the VentureXpert database. *ln experience companies* is measured as the logarithm of the total amount of companies invested in between the parent's first investment until the given investment date. *ln experience invested dollars* is captured by the logarithm of the aggregate dollars invested between the parent's first investment until the given investment date. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *Reputation* is the VCFs share of the IPO market, from 1980 until the date of investment, determined by the cumulative market capitalization of the dollar value of all companies taken public by the VCF, relative to other VCFs. *=1 if bull market* is a dummy variable which is equal to one the Nasdaq composite index went up during that calendar year, and zero otherwise. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *% increase Nasdaq* is the increase in the Nasdaq composite index between the first investment made by the fund and the current investment date. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Mean B/M* is the book-to-market ratio of public companies in the industry and year of investment and has not been included in the model except as interaction variable with *past performance* due to multicollinearity issues. *Downward stage drift* has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. *Upward stage drift* is equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. *Lagged downward drift rate* is the downward drift rate of the VC fund of all investments ten years prior to the current investment date. *Lagged upward drift rate* is the upward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	Bull market	1																	
(2)	=1 if during the dotcom bubble' * 'past performance'	-0.1152	1																
(3)	'Bull market' * 'past performance'	-0.0383	0.3803	1															
(4)	'Mean B/M' * 'past performance'	0.0312	-0.3273	0.0262	1														
(5)	'Mean P/E' * 'past performance'	-0.074	0.0787	-0.0484	-0.4018	1													
(6)	'Past performance' * 'ln VC inflows'	-0.1096	0.3231	-0.2771	-0.4934	0.1103	1												
(7)	'% increase Nasdaq' * 'past performance'	0.0713	-0.0284	-0.3133	-0.0731	0.0043	0.121	1											
(8)	Betweenness	0.0432	-0.0818	0.1006	0.0996	0.0004	-0.1365	-0.0441	1										
(9)	Degree	0.0281	-0.1073	0.0738	0.0751	0.005	-0.0521	-0.0185	0.9068	1									
(10)	Eigenvector	0.0328	-0.0886	0.1074	0.0898	0.0092	-0.1028	-0.0199	0.8487	0.9568	1								

(11)	Indegree	0.034	-0.1197	0.0456	0.0573	0.0003	-0.0128	-0.0024	0.8281	0.935	0.9057	1							
(12)	Company age	0.0602	-0.0399	-0.0455	-0.0272	-0.0031	0.0032	0.0379	-0.0881	-0.1213	-0.155	-0.1325	1						
(13)	Outdegree	0.0296	-0.0909	0.0328	0.043	0.0137	-0.0122	0.0022	0.9097	0.9452	0.8982	0.8727	-0.1172	1					
(14)	Lagged downward drift rate	-0.0138	-0.0295	0.1472	0.0208	0.0228	-0.0326	-0.0662	0.1888	0.2393	0.2169	0.2533	-0.0729	0.198	1				
(15)	Past performance	-0.1524	0.5876	0.8013	0.0476	-0.0229	-0.1898	-0.3628	0.0589	0.0228	0.0615	-0.0101	-0.0635	-0.0115	0.1006	1			
(16)	Lagged upward drift rate	-0.0218	0.059	-0.032	0.0001	-0.0119	-0.0522	-0.023	-0.0032	-0.04	-0.0328	-0.0507	-0.0578	-0.0615	-0.3962	0.0245	1		
(17)	Reputation	0.0578	-0.0656	0.1854	0.1487	-0.0329	-0.2064	-0.0797	0.6728	0.7337	0.7479	0.7279	-0.0582	0.6785	0.1831	0.155	-0.0251	1	
(18)	Downward drift	0.0203	-0.0297	0.0739	0.0416	0.0039	-0.0543	-0.0242	0.0954	0.1099	0.0985	0.1179	-0.2186	0.095	0.235	0.0423	-0.1233	0.0742	1
(19)	=1 if company from California	0.0402	0.026	0.0868	0.0039	-0.0082	-0.0089	-0.0056	0.1092	0.1795	0.2147	0.1832	-0.1728	0.1513	0.0929	0.0782	-0.0216	0.1312	0.0755
(20)	=1 if during the dotcom bubble	-0.21	0.4442	0.2217	-0.1701	0.0174	0.237	-0.0832	-0.0265	-0.0669	0.001	-0.0502	-0.0525	-0.0538	0.0028	0.3067	0.0626	-0.0162	-0.0498
(21)	=1 if during the dotcom bubble' * 'past performance'	-0.1152	1	0.3803	-0.3273	0.0787	0.3231	-0.0284	-0.0818	-0.1073	-0.0886	-0.1197	-0.0399	-0.0909	-0.0295	0.5876	0.059	-0.0656	-0.0297
(22)	=1 if first fund	-0.0317	0.1539	0.1443	-0.0003	-0.0217	-0.0436	-0.0275	-0.1398	-0.1813	-0.2203	-0.1583	0.0087	-0.1909	0.0688	0.1853	0.0294	-0.1366	0.0614
(23)	=1 if company from Massachusetts	-0.0105	-0.0226	-0.0007	0.0196	0.0063	-0.0185	-0.0432	-0.0156	-0.0084	0.0007	-0.0024	-0.0604	-0.0088	-0.0153	0.001	-0.0182	0.0093	0.0475
(24)	=1 if during the subprime mortgage crisis	-0.1968	-0.0713	-0.0741	-0.0424	0.0689	-0.0487	0.1022	-0.0259	-0.0385	-0.0187	-0.0368	-0.0063	0.0217	-0.0496	-0.1677	-0.0326	-0.0763	0.0354
(25)	VCF age	0.0244	-0.2129	-0.1523	0.0037	0.0017	0.0823	0.1125	0.2042	0.2855	0.3843	0.2849	-0.045	0.3128	-0.0552	-0.2289	-0.0635	0.2472	-0.0536
(26)	Mean P/E	0.0275	0.0401	0.0081	-0.0571	0.2254	0.063	-0.0274	0.021	0.0099	0.0464	0.0184	-0.0184	0.0012	-0.0094	0.0619	0.0265	0.0446	-0.0538
(27)	Fund sequence	0.0303	-0.1448	-0.0817	0.0042	0.0095	0.0654	0.0617	0.3477	0.4298	0.5086	0.4147	-0.0491	0.4654	-0.0505	-0.1422	-0.1022	0.4404	-0.042
(28)	Fund size	-0.0952	0.0049	-0.048	-0.0315	0.0217	0.0774	0.0079	0.1397	0.2071	0.2847	0.1126	-0.0338	0.2715	-0.091	-0.0153	-0.0445	0.1619	-0.0596
(29)	=1 if lead VC fund	-0.0566	0.0337	-0.0162	-0.0358	0.02	0.0159	0.0198	-0.0973	-0.1176	-0.1113	-0.1308	0.1031	-0.0943	-0.0361	0.0028	-0.0047	-0.0932	-0.0503
(30)	ln experience companies	0.0075	-0.2013	-0.1418	0.0233	0.0036	0.0715	0.0938	0.4762	0.6227	0.6898	0.5912	-0.0541	0.5897	0.0335	-0.2037	-0.0835	0.5207	-0.0102
(31)	ln experience invested dollars	-0.0265	-0.0528	-0.1109	-0.0446	0.0293	0.131	0.1077	0.3313	0.4611	0.5602	0.4052	-0.0772	0.4864	-0.06	-0.1145	-0.0829	0.3618	-0.0501
(32)	ln VC inflows	-0.1036	0.1668	-0.2183	-0.2182	0.0793	0.2683	0.1534	-0.2436	-0.2709	-0.1551	-0.2459	-0.0536	-0.144	-0.2428	-0.1582	0.032	-0.278	-0.1197
(33)	ln amount invested by syndicate	-0.0652	0.1022	-0.002	-0.0819	0.0203	0.127	0.0356	-0.0595	-0.0227	0.0408	-0.0569	0.0857	0.0184	-0.108	0.0413	-0.0524	0.0111	-0.2037
(34)	Number of VC funds in syndicate	-0.026	-0.0052	0.1127	0.0693	-0.0166	-0.0973	-0.0261	0.1273	0.1536	0.1599	0.1537	-0.1427	0.1044	0.1011	0.1123	-0.0025	0.1337	0.074
(35)	% increase Nasdaq	-0.0696	-0.0002	0.0272	-0.0163	-0.008	0.0564	-0.1457	0.008	0.0052	-0.0086	0.0172	-0.0087	-0.0152	0.0963	0.0165	0.0093	0.0224	0.0327
(36)	Upward drift	0.0152	0.0071	-0.0585	-0.0071	-0.0239	-0.0212	-0.006	-0.0162	-0.0354	-0.0349	-0.0448	0.2303	-0.0377	-0.1388	-0.0354	0.232	-0.0399	-0.327
(19)	=1 if company from California	1																	
(20)	=1 if during the dotcom bubble	-0.0128	1																
(21)	=1 if during the dotcom bubble' * 'past performance'	0.026	0.4442	1															
(22)	=1 if first fund	-0.0378	0.016	0.1539	1														
(23)	=1 if company from Massachusetts	-0.2805	-0.0273	-0.0226	0.0189	1													
(24)	=1 if during the subprime mortgage crisis	-0.0357	-0.1604	-0.0713	-0.0273	0.0163	1												

(25)	VCF age	0.0718	0.0327	-0.2129	-0.4749	0.0185	0.1345	1											
(26)	Mean P/E	0.0422	0.1768	0.0401	-0.0398	-0.0284	-0.1929	0.0562	1										
(27)	Fund sequence	0.0912	0.0227	-0.1448	-0.4383	0.002	0.1097	0.8096	0.0463	1									
(28)	Fund size	0.0374	0.0433	0.0049	-0.2346	0.0163	0.0868	0.4141	0.0308	0.4597	1								
(29)	=1 if lead VC fund	-0.0838	0.0605	0.0337	0.0194	-0.029	0.019	-0.0203	0.0273	-0.0508	0.0472	1							
(30)	ln experience companies	0.123	-0.0029	-0.2013	-0.3794	0.0161	0.0713	0.7213	0.0627	0.7478	0.4797	-0.0586	1						
(31)	ln experience invested dollars	0.1203	0.0638	-0.0528	-0.4051	-0.0012	0.1299	0.6621	0.0687	0.7007	0.6163	0.009	0.8585	1					
(32)	ln VC inflows	-0.0252	0.3649	0.1668	-0.1351	-0.0305	0.2319	0.3515	0.0817	0.2604	0.2975	0.1229	0.1688	0.431	1				
(33)	ln amount invested by syndicate	-0.0189	0.176	0.1022	-0.1599	-0.0108	0.0222	0.2388	0.0391	0.2386	0.3741	0.118	0.2115	0.4117	0.3453	1			
(34)	Number of VC funds in syndicate	0.0995	0.0113	-0.0052	0.0473	0.0141	-0.0851	-0.0564	-0.0159	-0.0194	-0.0879	-0.176	0.019	-0.0207	-0.1595	0.0957	1		
(35)	% increase Nasdaq	-0.0138	0.1919	-0.0002	0.3305	0.0416	-0.0801	-0.2394	0.0235	-0.2109	-0.1637	-0.0106	0.0085	-0.0854	-0.0093	-0.0571	0.0875	1	
(36)	Upward drift	-0.0655	-0.0141	0.0071	-0.0002	-0.0383	0.007	-0.0267	-0.004	-0.0413	-0.0324	0.0355	-0.0321	-0.0267	0.0301	0.0709	-0.0178	-0.0064	1

Appendix 2

Table 8:

Variance Inflation Factors of the Variables in Table 4

This table presents the variance inflation factors of the regression in Table 4. The dependent variable in this table is *downward stage drift*, which has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged downward drift rate* is the downward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are used.

	(1)	(2)	(3)	(4)	(5)
Company age	1.20	1.20	1.20	1.20	1.20
ln amount invested by syndicate	1.29	1.29	1.29	1.30	1.29
Number of VC funds in syndicate	1.15	1.15	1.15	1.15	1.15
=1 if company from California	1.20	1.19	1.20	1.21	1.19
=1 if company from Massachusetts	1.12	1.12	1.12	1.12	1.12
=1 if lead VC fund	1.09	1.09	1.09	1.09	1.09
=1 if first fund	1.18	1.18	1.18	1.18	1.18
Fund sequence	1.52	1.51	1.47	1.55	1.41
Past performance	1.49	1.49	1.49	1.49	1.49
=1 if during the dotcom bubble	1.54	1.53	1.54	1.54	1.55
=1 if during the subprime mortgage crisis	1.22	1.22	1.22	1.22	1.22
ln VC inflows	2.09	1.96	2.03	1.97	2.00
Mean P/E	1.28	1.28	1.28	1.28	1.28
Past performance ' * 'ln VC inflows'	1.32	1.32	1.33	1.33	1.33
Lagged downward drift rate	1.29	1.29	1.31	1.29	1.27
Degree	1.65				
Outdegree		1.50			
Indegree			1.59		
Eigenvector				1.69	
Betweenness					1.40

Table 9:

Variance Inflation Factors of the Variables in Table 5

This table presents the variance inflation factors of the regression in Table 5. The dependent variable in this table is *upward stage drift*, which has a value equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: c*ompany age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged upward drift rate* is the upward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are used.

	(1)	(2)	(3)	(4)	(5)
Company age	1.19	1.19	1.19	1.19	1.19
ln amount invested by syndicate	1.29	1.29	1.29	1.29	1.29
Number of VC funds in syndicate	1.15	1.15	1.15	1.15	1.15
=1 if company from California	1.20	1.19	1.20	1.21	1.19
=1 if company from Massachusetts	1.12	1.12	1.12	1.12	1.12
=1 if lead VC fund	1.09	1.09	1.09	1.09	1.09
=1 if first fund	1.18	1.18	1.18	1.18	1.18
Fund sequence	1.51	1.51	1.47	1.55	1.42
Past performance	1.49	1.49	1.48	1.49	1.49
=1 if during the dotcom bubble	1.53	1.52	1.53	1.53	1.54
=1 if during the subprime mortgage crisis	1.22	1.22	1.22	1.22	1.22
ln VC inflows	2.03	1.88	1.98	1.90	1.92
Mean P/E	1.28	1.28	1.28	1.28	1.28
Past performance ' * 'ln VC inflows'	1.32	1.33	1.33	1.33	1.33
Lagged upward drift rate	1.25	1.25	1.25	1.25	1.25
Degree	1.58				
Outdegree		1.45			
Indegree			1.51		
Eigenvector				1.62	
Betweenness					1.37

Appendix 3

Table 10:
Effect of Reputation on Downward Stage Drift

The dependent variable in this table is *downward stage drift*, which has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Reputation* is the VCFs share of the IPO market, from 1980 until the date of investment, determined by the cumulative market capitalization of the dollar value of all companies taken public by the VCF, relative to other VCFs. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged downward drift rate* is the downward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Company and investment characteristics						
Company age	-0.570***	-0.570***	-0.568***	-0.566***	-0.575***	-0.576***
	(0.0509)	(0.0509)	(0.0507)	(0.0507)	(0.0510)	(0.0510)
ln amount invested by syndicate	-0.349***	-0.348***	-0.343***	-0.353***	-0.341***	-0.343***
	(0.0253)	(0.0252)	(0.0252)	(0.0253)	(0.0251)	(0.0250)
Number of VC funds in syndicate	0.0311**	0.0335**	0.0302**	0.0309**	0.0324**	0.0341**
	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)
=1 if company from California	0.207***	0.221***	0.202***	0.192***	0.233***	0.231***
	(0.0660)	(0.0660)	(0.0661)	(0.0662)	(0.0660)	(0.0659)
=1 if company from Massachusetts	0.282***	0.285***	0.279***	0.273***	0.289***	0.277***
	(0.0953)	(0.0952)	(0.0954)	(0.0952)	(0.0953)	(0.0952)
=1 if lead VC fund	0.0540	0.0542	0.0602	0.0555	0.0540	0.0489
	(0.0881)	(0.0882)	(0.0882)	(0.0884)	(0.0881)	(0.0881)
VC fund and VCF characteristics						
=1 if first fund	0.183**	0.175**	0.170**	0.200**	0.163*	0.138
	(0.0869)	(0.0865)	(0.0866)	(0.0876)	(0.0862)	(0.0860)
Past performance	-0.0746	-0.0835	-0.0421	-0.0991	-0.108	-0.128
	(0.126)	(0.125)	(0.126)	(0.126)	(0.124)	(0.124)
Reputation	-0.0756	-0.0486	-0.100	-0.0962	-0.00338	0.131***
	(0.0647)	(0.0615)	(0.0679)	(0.0664)	(0.0577)	(0.0455)
Fund inflows and market conditions						
=1 if during the dotcom bubble	0.0111	0.0278	0.00273	-0.00544	-0.00696	0.0148
	(0.0869)	(0.0869)	(0.0868)	(0.0871)	(0.0869)	(0.0866)
=1 if during the subprime mortgage crisis	0.396***	0.385***	0.396***	0.392***	0.400***	0.420***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
ln VC inflows	-0.0730**	-0.0977***	-0.0799**	-0.0964***	-0.0877**	-0.102***
	(0.0364)	(0.0359)	(0.0362)	(0.0359)	(0.0360)	(0.0357)
Mean P/E	-0.00898**	-0.00888**	-0.00907**	-0.00933**	-0.00934**	-0.00876**
	(0.00368)	(0.00368)	(0.00367)	(0.00367)	(0.00367)	(0.00366)
'Past performance' * 'ln VC inflows'	0.0121	0.0151	-0.0163	0.0622	0.0838	0.0783
	(0.0859)	(0.0857)	(0.0868)	(0.0852)	(0.0850)	(0.0848)
Persistence						
Lagged downward drift rate	0.990***	0.996***	0.966***	0.988***	1.031***	1.055***
	(0.133)	(0.132)	(0.133)	(0.133)	(0.132)	(0.132)

Resource access measures						
Degree	0.0645***					
	(0.0139)					
Outdegree		0.0337***				
		(0.00750)				
Indegree			0.0634***			
			(0.0134)			
Eigenvector				0.0362***		
				(0.00756)		
Betweenness					0.175***	
					(0.0458)	
Intercept						
Constant	0.0329	0.194	0.0841	0.123	0.199	0.290
	(0.245)	(0.239)	(0.242)	(0.241)	(0.238)	(0.236)
Diagnostics						
Observations	6,432	6,432	6,432	6,432	6,432	6,432
Pseudo R-squared	0.165	0.165	0.165	0.165	0.164	0.162
Log likelihood	-3409	-3410	-3408	-3409	-3413	-3420

Table 11:

Effect of Reputation on Upward Stage Drift

The dependent variable in this table is *upward stage drift*, which is equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Reputation* is the VCFs share of the IPO market, from 1980 until the date of investment, determined by the cumulative market capitalization of the dollar value of all companies taken public by the VCF, relative to other VCFs. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged upward drift rate* is the upward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Company and investment characteristics						
Company age	0.679***	0.679***	0.680***	0.678***	0.680***	0.680***
	(0.0486)	(0.0486)	(0.0485)	(0.0485)	(0.0486)	(0.0486)
ln amount invested by syndicate	0.306***	0.306***	0.303***	0.312***	0.300***	0.301***
	(0.0364)	(0.0365)	(0.0365)	(0.0367)	(0.0364)	(0.0364)
Number of VC funds in syndicate	0.0114	0.0104	0.0145	0.0112	0.00952	0.00839
	(0.0187)	(0.0187)	(0.0188)	(0.0187)	(0.0187)	(0.0186)
=1 if company from California	-0.292***	-0.298***	-0.284***	-0.281***	-0.303***	-0.302***
	(0.0811)	(0.0810)	(0.0813)	(0.0815)	(0.0810)	(0.0810)
=1 if company from Massachusetts	-0.258**	-0.260**	-0.257**	-0.252**	-0.257**	-0.253**
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
=1 if lead VC fund	0.0924	0.0935	0.0869	0.0886	0.0964	0.0982
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
VC fund and VCF characteristics						
=1 if first fund	-0.135	-0.134	-0.132	-0.150	-0.119	-0.111
	(0.114)	(0.113)	(0.113)	(0.114)	(0.114)	(0.113)

Past performance	0.200	0.198	0.145	0.207	0.224	0.233
	(0.154)	(0.154)	(0.155)	(0.153)	(0.154)	(0.154)
Reputation	0.112	0.121	0.214**	0.145	0.0259	-0.0203
	(0.0872)	(0.0832)	(0.0918)	(0.0897)	(0.0775)	(0.0598)
Fund inflows and market conditions						
=1 if during the dotcom bubble	-0.171	-0.183	-0.157	-0.161	-0.171	-0.179
	(0.113)	(0.113)	(0.114)	(0.114)	(0.113)	(0.113)
=1 if during the subprime mortgage crisis	-0.0693	-0.0572	-0.0617	-0.0657	-0.0779	-0.0852
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
ln VC inflows	0.0311	0.0448	0.0252	0.0425	0.0441	0.0499
	(0.0448)	(0.0444)	(0.0448)	(0.0445)	(0.0445)	(0.0443)
Mean P/E	0.000477	0.000321	0.000661	0.000819	0.000373	0.000248
	(0.00464)	(0.00465)	(0.00467)	(0.00465)	(0.00464)	(0.00464)
'Past performance' * 'ln VC inflows'	-0.345***	-0.333***	-0.302***	-0.375***	-0.382***	-0.385***
	(0.107)	(0.107)	(0.107)	(0.106)	(0.106)	(0.106)
Persistence						
Lagged upward drift rate	0.809***	0.799***	0.743***	0.793***	0.857***	0.865***
	(0.182)	(0.182)	(0.182)	(0.182)	(0.181)	(0.180)
Resource access measures						
Degree	-0.0395**					
	(0.0186)					
Outdegree		-0.0254**				
		(0.0103)				
Indegree			-0.0628***			
			(0.0190)			
Eigenvector				-0.0248**		
				(0.0101)		
Betweenness					-0.0573	
					(0.0608)	
Intercept						
Constant	-3.128***	-3.200***	-3.056***	-3.156***	-3.265***	-3.303***
	(0.308)	(0.302)	(0.306)	(0.306)	(0.302)	(0.301)
Diagnostics						
Observations	5,781	5,781	5,781	5,781	5,781	5,781
Pseudo R-squared	0.220	0.220	0.221	0.220	0.219	0.219
Log likelihood	-2409	-2408	-2405	-2408	-2411	-2411

Appendix 4

Table 12:
Effect of Resource Access on Downward Stage Drift Excluding Persistence

The dependent variable in this table is *downward stage drift*, which has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
Company and investment characteristics					
Company age	-0.582***	-0.583***	-0.580***	-0.578***	-0.589***
	(0.0501)	(0.0502)	(0.0499)	(0.0499)	(0.0504)
ln amount invested by syndicate	-0.354***	-0.353***	-0.348***	-0.358***	-0.344***
	(0.0246)	(0.0246)	(0.0246)	(0.0247)	(0.0244)
Number of VC funds in syndicate	0.0348**	0.0378***	0.0339**	0.0347**	0.0372***
	(0.0139)	(0.0139)	(0.0139)	(0.0139)	(0.0139)
=1 if company from California	0.232***	0.250***	0.226***	0.215***	0.270***
	(0.0643)	(0.0641)	(0.0643)	(0.0645)	(0.0640)
=1 if company from Massachusetts	0.278***	0.282***	0.273***	0.268***	0.286***
	(0.0926)	(0.0924)	(0.0927)	(0.0926)	(0.0925)
=1 if lead VC fund	0.0635	0.0640	0.0722	0.0643	0.0654
	(0.0857)	(0.0857)	(0.0857)	(0.0860)	(0.0856)
VC fund and VCF characteristics					
=1 if first fund	0.240***	0.228***	0.230***	0.257***	0.229***
	(0.0854)	(0.0851)	(0.0853)	(0.0858)	(0.0850)
Fund sequence	-0.0128	-0.0119	-0.0112	-0.0149	-0.00260
	(0.00956)	(0.00952)	(0.00938)	(0.00970)	(0.00909)
Past performance	-0.118	-0.122	-0.0882	-0.148	-0.138
	(0.119)	(0.118)	(0.119)	(0.120)	(0.118)
Fund inflows and market conditions					
=1 if during the dotcom bubble	0.0718	0.0943	0.0619	0.0521	0.0664
	(0.0845)	(0.0844)	(0.0844)	(0.0848)	(0.0844)
=1 if during the subprime mortgage crisis	0.398***	0.384***	0.398***	0.394***	0.402***
	(0.105)	(0.106)	(0.106)	(0.106)	(0.106)
ln VC inflows	-0.109***	-0.142***	-0.116***	-0.132***	-0.147***
	(0.0357)	(0.0342)	(0.0352)	(0.0345)	(0.0344)
Mean P/E	-0.00875**	-0.00863**	-0.00886**	-0.00916**	-0.00912**
	(0.00361)	(0.00361)	(0.00361)	(0.00361)	(0.00361)
'Past performance' * 'ln VC inflows'	0.0451	0.0396	0.0224	0.105	0.106
	(0.0820)	(0.0817)	(0.0819)	(0.0823)	(0.0822)
Resource access measures					
Degree	0.0740***				
	(0.0112)				
Outdegree		0.0408***			
		(0.00638)			
Indegree			0.0678***		
			(0.0100)		

	(1)	(2)	(3)	(4)	(5)
Eigenvector				0.0399***	
				(0.00595)	
Betweenness					0.214***
					(0.0402)
Intercept					
Constant	0.538**	0.737***	0.586***	0.636***	0.793***
	(0.225)	(0.217)	(0.222)	(0.220)	(0.216)
Diagnostics					
Observations	6,648	6,648	6,648	6,648	6,648
Pseudo R-squared	0.157	0.156	0.157	0.157	0.155
Log likelihood	-3556	-3557	-3554	-3555	-3563

Table 13:

Effect of Resource Access on Upward Stage Drift Excluding Persistence

The dependent variable in this table is *upward stage drift*, which is equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *degree* is the number of distinct VCFs it has syndicated with (regardless of the role in the syndicate). A VCF's *outdegree* is the number of times that the VCF has led syndicates where others were non-lead investors, and its *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. The *eigenvector* measures how close a given VCF is to all other VCFs, and *betweenness* is the number of shortest-distance paths between the VCF and other VCFs in its network. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
Company and investment characteristics					
Company age	0.685***	0.685***	0.684***	0.684***	0.687***
	(0.0487)	(0.0487)	(0.0486)	(0.0487)	(0.0487)
ln amount invested by syndicate	0.308***	0.309***	0.309***	0.312***	0.304***
	(0.0359)	(0.0360)	(0.0360)	(0.0362)	(0.0358)
Number of VC funds in syndicate	0.0112	0.0109	0.0134	0.0112	0.00954
	(0.0185)	(0.0184)	(0.0185)	(0.0184)	(0.0184)
=1 if company from California	-0.299***	-0.301***	-0.288***	-0.292***	-0.310***
	(0.0797)	(0.0795)	(0.0799)	(0.0800)	(0.0794)
=1 if company from Massachusetts	-0.259**	-0.260**	-0.256**	-0.256**	-0.257**
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
=1 if lead VC fund	0.0782	0.0783	0.0728	0.0760	0.0820
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)
VC fund and VCF characteristics					
=1 if first fund	-0.178	-0.176	-0.178	-0.185	-0.171
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
Fund sequence	-0.0133	-0.0111	-0.00715	-0.0109	-0.0209*
	(0.0127)	(0.0127)	(0.0125)	(0.0129)	(0.0122)
Past performance	0.260*	0.260*	0.240	0.268*	0.265*
	(0.146)	(0.146)	(0.146)	(0.146)	(0.147)
Fund inflows and market conditions					
=1 if during the dotcom bubble	-0.145	-0.150	-0.128	-0.136	-0.157
	(0.112)	(0.111)	(0.112)	(0.112)	(0.112)
=1 if during the subprime mortgage crisis	-0.105	-0.0963	-0.0976	-0.103	-0.113
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)

ln VC inflows	0.0512	0.0555	0.0342	0.0539	0.0739*
	(0.0451)	(0.0435)	(0.0450)	(0.0440)	(0.0439)
Mean P/E	-0.000351	-0.000440	-0.000260	-0.000174	-0.000412
	(0.00456)	(0.00456)	(0.00459)	(0.00457)	(0.00455)
'Past performance' * 'ln VC inflows'	-0.424***	-0.418***	-0.415***	-0.445***	-0.428***
	(0.104)	(0.104)	(0.104)	(0.105)	(0.104)
Resource access measures					
Degree	-0.0227				
	(0.0146)				
Outdegree		-0.0161*			
		(0.00844)			
Indegree			-0.0365***		
			(0.0139)		
Eigenvector				-0.0139*	
				(0.00774)	
Betweenness					-0.0213
					(0.0520)
Intercept					
Constant	-3.011***	-3.043***	-2.935***	-3.021***	-3.128***
	(0.301)	(0.295)	(0.299)	(0.299)	(0.295)
Diagnostics					
Observations	5,915	5,915	5,915	5,915	5,915
Pseudo R-squared	0.216	0.216	0.217	0.216	0.216
Log likelihood	-2476	-2475	-2473	-2476	-2477

Appendix 5

Table 14:

Effect of Different Experience Measures on Downward Stage Drift

The dependent variable in this table is *downward stage drift*, which has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead investor in that round. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged downward drift rate* is the downward drift rate of the VC fund of all investments ten years prior to the current investment date. *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. *ln experience companies* is measured as the logarithm of the total amount of companies invested in between the parent's first investment until the given investment date. *ln experience invested dollars* is captured by the logarithm of the aggregate dollars invested between the parent's first investment until the given investment date. *VCF age* is measured as the amount of years between the first investment made by the fund and the first investment made by the fund's parent. *Fund size* is the amount of capital committed reported in the VentureXpert database. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
Company and investment characteristics					
Company age	-0.577***	-0.576***	-0.574***	-0.577***	-0.527***
	(0.0511)	(0.0512)	(0.0513)	(0.0511)	(0.0522)
ln amount invested by syndicate	-0.339***	-0.340***	-0.345***	-0.337***	-0.354***
	(0.0249)	(0.0251)	(0.0261)	(0.0248)	(0.0282)
Number of VC funds in syndicate	0.0351**	0.0348**	0.0353**	0.0352**	0.0382**
	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0158)
=1 if company from California	0.244***	0.239***	0.238***	0.247***	0.266***
	(0.0657)	(0.0659)	(0.0659)	(0.0656)	(0.0726)
=1 if company from Massachusetts	0.278***	0.278***	0.278***	0.278***	0.326***
	(0.0951)	(0.0951)	(0.0952)	(0.0952)	(0.105)
=1 if lead VC fund	0.0473	0.0443	0.0429	0.0416	0.0250
	(0.0883)	(0.0881)	(0.0880)	(0.0881)	(0.0979)
Fund inflows and market conditions					
=1 if during the dotcom bubble	0.0359	0.0309	0.0443	0.0316	0.0127
	(0.0866)	(0.0866)	(0.0874)	(0.0865)	(0.0965)
=1 if during the subprime mortgage crisis	0.423***	0.421***	0.419***	0.425***	0.551***
	(0.108)	(0.108)	(0.108)	(0.108)	(0.126)
ln VC inflows	-0.133***	-0.128***	-0.140***	-0.133***	-0.0855**
	(0.0349)	(0.0347)	(0.0358)	(0.0351)	(0.0382)
Mean P/E	-0.00857**	-0.00864**	-0.00857**	-0.00861**	-0.00577
	(0.00365)	(0.00366)	(0.00366)	(0.00366)	(0.00401)
'Past performance' * 'ln VC inflows'	0.0437	0.0416	0.0393	0.0461	0.118
	(0.0842)	(0.0843)	(0.0844)	(0.0841)	(0.0925)
Persistence					
Lagged downward drift rate	1.085***	1.082***	1.090***	1.084***	1.208***
	(0.131)	(0.131)	(0.131)	(0.131)	(0.143)
VC fund and VCF characteristics					
=1 if first fund	0.142	0.129	0.138	0.131	0.0959
	(0.0893)	(0.0879)	(0.0889)	(0.0894)	(0.0889)
Past performance	-0.0998	-0.0784	-0.103	-0.0916	-0.0882
	(0.124)	(0.125)	(0.124)	(0.124)	(0.141)
Fund sequence	0.0141*				
	(0.00827)				
ln experience companies		0.0433			
		(0.0298)			
ln experience invested dollars			0.0360		
			(0.0233)		
VCF age				0.00551	

				(0.00440)	
Fund size					6.57e-05
					(0.000145)
Intercept					
Constant	0.371	0.248	0.294	0.391*	0.0871
	(0.233)	(0.260)	(0.247)	(0.232)	(0.251)
Diagnostics					
Observations	6,432	6,432	6,432	6,432	5,187
Pseudo R-squared	0.161	0.161	0.161	0.161	0.160
Log likelihood	-3423	-3423	-3423	-3424	-2804

Table 15:

Effect of Different Experience Measures on Upward Stage Drift

The dependent variable in this table is *upward stage drift*, which is equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead investor in that round. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Lagged upward drift rate* is the upward drift rate of the VC fund of all investments ten years prior to the current investment date. *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. *ln experience companies* is measured as the logarithm of the total amount of companies invested in between the parent's first investment until the given investment date. *ln experience invested dollars* is captured by the logarithm of the aggregate dollars invested between the parent's first investment until the given investment date. *VCF age* is measured as the amount of years between the first investment made by the fund and the first investment made by the fund's parent. *Fund size* is the amount of capital committed reported in the VentureXpert database. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
Company and investment characteristics					
Company age	0.679***	0.681***	0.680***	0.680***	0.657***
	(0.0484)	(0.0488)	(0.0489)	(0.0485)	(0.0513)
ln amount invested by syndicate	0.306***	0.298***	0.303***	0.301***	0.342***
	(0.0365)	(0.0365)	(0.0382)	(0.0363)	(0.0441)
Number of VC funds in syndicate	0.00825	0.00823	0.00807	0.00814	0.00776
	(0.0186)	(0.0186)	(0.0186)	(0.0186)	(0.0213)
=1 if company from California	-0.297***	-0.306***	-0.302***	-0.302***	-0.285***
	(0.0808)	(0.0812)	(0.0811)	(0.0808)	(0.0919)
=1 if company from Massachusetts	-0.245*	-0.255**	-0.252**	-0.250**	-0.309**
	(0.125)	(0.126)	(0.125)	(0.126)	(0.141)
=1 if lead VC fund	0.0930	0.1000	0.0988	0.0979	0.147
	(0.106)	(0.106)	(0.106)	(0.106)	(0.123)
Fund inflows and market conditions					
=1 if during the dotcom bubble	-0.188*	-0.181	-0.187	-0.182	-0.139
	(0.113)	(0.113)	(0.115)	(0.113)	(0.128)
=1 if during the subprime mortgage crisis	-0.0784	-0.0881	-0.0846	-0.0845	-0.0410
	(0.125)	(0.125)	(0.125)	(0.125)	(0.154)
ln VC inflows	0.0596	0.0537	0.0575	0.0564	0.0300
	(0.0425)	(0.0426)	(0.0438)	(0.0427)	(0.0484)
Mean P/E	0.000458	0.000182	0.000277	0.000337	-0.00253
	(0.00463)	(0.00465)	(0.00464)	(0.00463)	(0.00512)
'Past performance' * 'ln VC inflows'	-0.378***	-0.379***	-0.377***	-0.379***	-0.501***
	(0.105)	(0.106)	(0.106)	(0.106)	(0.117)
Persistence					
Lagged upward drift rate	0.836***	0.872***	0.862***	0.863***	1.109***
	(0.182)	(0.183)	(0.182)	(0.181)	(0.201)

VC fund and VCF characteristics					
=1 if first fund	-0.156	-0.101	-0.116	-0.122	-0.0413
	(0.116)	(0.116)	(0.117)	(0.116)	(0.117)
Past performance	0.224	0.232	0.230	0.222	0.0478
	(0.153)	(0.155)	(0.154)	(0.154)	(0.179)
Fund sequence	-0.0176				
	(0.0112)				
ln experience companies		0.00520			
		(0.0374)			
ln experience invested dollars			-0.0101		
			(0.0291)		
VCF age				-0.00291	
				(0.00524)	
Fund size					-0.000224
					(0.000200)
Intercept					
Constant	-3.262***	-3.344***	-3.289***	-3.307***	-3.125***
	(0.299)	(0.332)	(0.313)	(0.298)	(0.333)
Diagnostics					
Observations	5,781	5,781	5,781	5,781	4,586
Pseudo R-squared	0.220	0.219	0.219	0.219	0.223
Log likelihood	-2410	-2411	-2411	-2411	-1875

Appendix 6

Table 16:

Effect of Different Market Conditions on Downward Stage Drift

The dependent variable in this table is *downward stage drift*, which has a value equal to one if an investment was in an earlier stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *Lagged downward drift rate* is the downward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *% increase Nasdaq* is the increase in the Nasdaq composite index between the first investment made by the fund and the current investment date. *=1 if bull market* is a dummy variable which is equal to one the Nasdaq composite index went up during that calendar year, and zero otherwise. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Mean B/M* is the book-to-market ratio of public companies in the industry and year of investment and has not been included in the model except as interaction variable with *past performance* due to multicollinearity issues. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Company and investment characteristics							
Company age	-0.570***	-0.569***	-0.571***	-0.570***	-0.569***	-0.569***	-0.569***
	(0.0507)	(0.0506)	(0.0508)	(0.0508)	(0.0507)	(0.0507)	(0.0506)
ln amount invested by syndicate	-0.342***	-0.341***	-0.341***	-0.340***	-0.344***	-0.344***	-0.342***
	(0.0251)	(0.0251)	(0.0251)	(0.0251)	(0.0252)	(0.0252)	(0.0251)
Number of VC funds in syndicate	0.0308**	0.0308**	0.0318**	0.0316**	0.0301**	0.0300**	0.0306**
	(0.0142)	(0.0142)	(0.0142)	(0.0143)	(0.0142)	(0.0142)	(0.0142)
=1 if company from California	0.205***	0.205***	0.195***	0.195***	0.202***	0.202***	0.202***
	(0.0660)	(0.0661)	(0.0662)	(0.0662)	(0.0661)	(0.0660)	(0.0660)
=1 if company from Massachusetts	0.288***	0.287***	0.281***	0.282***	0.278***	0.278***	0.282***
	(0.0953)	(0.0954)	(0.0950)	(0.0951)	(0.0955)	(0.0954)	(0.0952)
=1 if lead VC fund	0.0544	0.0512	0.0668	0.0643	0.0554	0.0576	0.0533
	(0.0880)	(0.0880)	(0.0883)	(0.0883)	(0.0882)	(0.0882)	(0.0880)
VC fund and VCF characteristics							
=1 if first fund	0.172*	0.171*	0.171*	0.170*	0.159*	0.159*	0.162*
	(0.0893)	(0.0896)	(0.0890)	(0.0892)	(0.0892)	(0.0891)	(0.0893)
Fund sequence	-0.0133	-0.0135	-0.00904	-0.00958	-0.00843	-0.00874	-0.00892
	(0.0102)	(0.0102)	(0.00953)	(0.00954)	(0.00954)	(0.00955)	(0.00956)
Past performance	-0.0923	-0.0972	-0.0512	-0.213	-0.0760	-0.0753	-0.0797
	(0.123)	(0.125)	(0.124)	(0.201)	(0.123)	(0.123)	(0.146)
Persistence							
Lagged downward drift rate	0.961***	0.966***	0.963***	0.959***	0.963***	0.967***	0.964***
	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)
Resource access measures							
Indegree	0.0558***	0.0561***	0.0526***	0.0526***	0.0534***	0.0535***	0.0527***
	(0.0105)	(0.0105)	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)
Fund inflows and market conditions							
=1 if during the dotcom bubble	-0.00703	-0.00772	0.00576	-0.00306	-0.00127	-0.00234	-0.0246
	(0.0867)	(0.0868)	(0.0870)	(0.0872)	(0.0860)	(0.0864)	(0.0880)
=1 if during the subprime mortgage crisis	0.451***	0.452***	0.510***	0.492***	0.385***	0.397***	0.455***
	(0.104)	(0.104)	(0.107)	(0.108)	(0.108)	(0.107)	(0.104)
ln VC inflows	-0.0640*	-0.0635*	-0.0698*	-0.0649*	-0.0679*	-0.0654*	-0.0699*
	(0.0364)	(0.0367)	(0.0361)	(0.0364)	(0.0362)	(0.0366)	(0.0367)
% increase Nasdaq	-0.0113	-0.0121					
	(0.00872)	(0.00917)					
'Past performance' * '% increase Nasdaq'		-0.00979					

		(0.0649)					
=1 if bull market			0.134**	0.125*			
			(0.0671)	(0.0677)			
'Past performance' * '=1 if bull market'				0.243			
				(0.238)			
Mean P/E					-0.0101***	-0.00906**	
					(0.00382)	(0.00368)	
'Past performance' * 'Mean P/E'					0.0130		
					(0.0118)		
'Past performance' * 'Mean B/M'						0.0589	
						(0.492)	
'Past performance' * '=1 if during the dotcom bubble'							0.00305
							(0.261)
Intercept							
Constant	-0.0667	-0.0680	-0.183	-0.127	0.102	0.0747	-0.0660
	(0.231)	(0.231)	(0.238)	(0.245)	(0.240)	(0.240)	(0.237)
Diagnostics							
Observations	6,436	6,432	6,436	6,432	6,432	6,432	6,432
Pseudo R-squared	0.164	0.164	0.165	0.165	0.165	0.165	0.164
Log likelihood	-3414	-3411	-3413	-3410	-3409	-3409	-3412

Table 17:

Effect of Different Market Conditions on Upward Stage Drift

The dependent variable in this table is *upward stage drift*, which is equal to one if an investment was in a later stage of development than the stated fund focus, and zero otherwise. The independent variables are as follows: *company age* is the age of the portfolio company in months. The *ln amount invested by syndicate* measures the logarithm of the total amount invested by all VC funds in the portfolio company in that round, in millions of dollars and *number of VC funds in syndicate* is the amount of VC funds investing in the portfolio company in that round. The two variables *=1 if company from California* and *=1 if company from Massachusetts* are dummy variables equal to zero for all companies outside of these locations. *=1 is lead VC fund* is a dummy variable equal to one if the fund is the lead VC fund in that round and *=1 if first fund* is a dummy variable equal to one if the fund is the VCF's first. *Fund sequence* is the number of VC funds raised by the VCF, i.e. whether the specified fund is the VCF's first, second, and so forth. The *past performance* is the fund's previous performance, measured as the ratio of successful exits by means of an IPO over all investments up to date which have could have had an exit. *Lagged upward drift rate* is the upward drift rate of the VC fund of all investments ten years prior to the current investment date. The network measures are constructed from adjacency matrices using all VCF syndicate investments in the five years prior to the current investment year. Networks are measured as relationships among VCFs, not among VC funds, such that a new fund can benefit from its parent's existing network connections. A VCF's *indegree* is the number of times a VCF participated in a syndicate as non-lead investor. *=1 if during the dotcom bubble* is a dummy equal to one in the years 1998 to 2000 (inclusive), while *=1 if during subprime mortgage crisis* is a dummy equal to one in the years 2008 and 2009, both zero if the condition does not apply. *ln VC inflows* is the logarithm of the aggregate amount of capital raised by other VC funds in the year of investment. *% increase Nasdaq* is the increase in the Nasdaq composite index between the first investment made by the fund and the current investment date. *=1 if bull market* is a dummy variable which is equal to one the Nasdaq composite index went up during that calendar year, and zero otherwise. *Mean P/E* is the price-to-earnings ratio of *public* companies in the industry and year of investment. *Mean B/M* is the book-to-market ratio of public companies in the industry and year of investment and has not been included in the model except as interaction variable with *past performance* due to multicollinearity issues. Dummy variables for the fund stage and for industry effects using the VentureXpert industry groups are included in analysis but not reported. Heteroscedasticity-consistent White-Huber standard errors are shown in brackets. I use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Company and investment characteristics							
Company age	0.675***	0.675***	0.674***	0.674***	0.675***	0.675***	0.674***
	(0.0483)	(0.0482)	(0.0482)	(0.0482)	(0.0483)	(0.0482)	(0.0482)
ln amount invested by syndicate	0.299***	0.300***	0.302***	0.302***	0.301***	0.303***	0.301***
	(0.0366)	(0.0366)	(0.0366)	(0.0366)	(0.0366)	(0.0367)	(0.0366)
Number of VC funds in syndicate	0.0174	0.0177	0.0177	0.0177	0.0167	0.0154	0.0168
	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)
=1 if company from California	-0.283***	-0.283***	-0.282***	-0.283***	-0.283***	-0.282***	-0.281***
	(0.0811)	(0.0811)	(0.0811)	(0.0810)	(0.0810)	(0.0811)	(0.0810)
=1 if company from Massachusetts	-0.250**	-0.254**	-0.247**	-0.248**	-0.248**	-0.246**	-0.246**
	(0.126)	(0.126)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
=1 if lead VC fund	0.0893	0.0911	0.0935	0.0956	0.0951	0.0884	0.0893
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
VC fund and VCF characteristics							
=1 if first fund	-0.172	-0.168	-0.171	-0.172	-0.175	-0.167	-0.170

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
Fund sequence	-0.000514	-0.00136	-0.00468	-0.00477	-0.00553	-0.00522	-0.00517
	(0.0134)	(0.0135)	(0.0125)	(0.0126)	(0.0125)	(0.0125)	(0.0126)
Past performance	0.289*	0.255	0.304**	0.289	0.285*	0.279*	0.336*
	(0.150)	(0.156)	(0.153)	(0.238)	(0.150)	(0.150)	(0.174)
Persistence							
Lagged upward drift rate	0.857***	0.856***	0.853***	0.851***	0.843***	0.835***	0.850***
	(0.181)	(0.181)	(0.181)	(0.182)	(0.181)	(0.182)	(0.181)
Resource access measures							
Indegree	-0.0335**	-0.0326**	-0.0303**	-0.0304**	-0.0298**	-0.0307**	-0.0309**
	(0.0145)	(0.0145)	(0.0138)	(0.0138)	(0.0138)	(0.0139)	(0.0139)
Fund inflows and market conditions							
=1 if during the dotcom bubble	-0.251**	-0.245**	-0.222*	-0.221*	-0.246**	-0.222**	-0.226*
	(0.111)	(0.111)	(0.113)	(0.114)	(0.112)	(0.112)	(0.116)
=1 if during the subprime mortgage crisis	-0.0219	-0.0217	0.0108	0.00816	0.00996	-0.0139	-0.0204
	(0.122)	(0.122)	(0.126)	(0.127)	(0.125)	(0.124)	(0.121)
ln VC inflows	-0.00428	-0.00129	-0.000175	0.000499	0.00445	0.00763	0.00462
	(0.0460)	(0.0459)	(0.0454)	(0.0461)	(0.0455)	(0.0454)	(0.0457)
% increase Nasdaq	0.00914	0.00580					
	(0.0104)	(0.0111)					
'Past performance' * '% increase Nasdaq'		-0.0729					
		(0.0838)					
=1 if bull market			0.0771	0.0752			
			(0.0863)	(0.0869)			
'Past performance' * '=1 if bull market'				0.0225			
				(0.287)			
Mean P/E					0.00239	0.000435	
					(0.00472)	(0.00468)	
'Past performance' * 'Mean P/E'					-0.0298**		
					(0.0149)		
'Past performance' * 'Mean B/M'						0.939	
						(0.603)	
'Past performance' * '=1 if during the dotcom bubble'							-0.179
							(0.323)
Intercept							
Constant	-2.991***	-2.988***	-3.054***	-3.048***	-3.036***	-3.019***	-3.021***
	(0.292)	(0.292)	(0.303)	(0.306)	(0.304)	(0.301)	(0.297)
Diagnostics							
Observations	5,783	5,781	5,783	5,781	5,781	5,781	5,781
Pseudo R-squared	0.219	0.219	0.219	0.219	0.219	0.219	0.219
Log likelihood	-2414	-2413	-2414	-2414	-2412	-2413	-2414