Journal of Business Venturing, Volume 32, Issue 5, September 2017, Pages 519-535
DOI:10.1016/j.jbusvent.2017.05.005

Diversification, Risk, and Returns in Venture Capital

Axel Buchner
University of Passau, Germany

Abdulkadir Mohamed
Cranfield – School of Management, United Kingdom

Armin Schwienbacher
SKEMA Business School – Université Côte d'Azur, France

ABSTRACT
We explore an alternative, finance theory-based explanation for the documented positive relationship between fund diversification (or lack of fund specialization) and performance in venture capital (VC). Our proposed "Risk Hypothesis" posits that the expected negative impact of diversification on fund risk induces fund managers to endogenously select riskier investments, which in turn leads to higher performance of more diversified funds. While other channels may also be at play, we provide results that support this hypothesis for an international sample of VC funds. However, this effect is weakened when expertise is limited. The study offers implications of how VC fund managers' investment decisions are influenced by strategic portfolio considerations, which in turn affect which innovative ventures receive funding.

Keywords: Venture capital; Diversification; Risk; Entrepreneurial finance; Venture finance

JEL Classifications: G24; G23

---

* Contact details of authors: Axel Buchner, University of Passau, Department of Business and Economics, University of Passau, 94030 Passau, Germany, email: axel.buchner@uni-passau.de, phone: +49 8515093245; Abdulkadir Mohamed, Cranfield School of Management, College Road, Cranfield MK43 0AL, United Kingdom, email: abdulkadir.mohamed@cranfield.ac.uk; phone: +44 1234 751122; Armin Schwienbacher, SKEMA Business School, Lille Campus, Department of Finance and Accounting, Avenue Willy Brandt, 59777 Euralille, France, email: armin.schwienbacher@skema.edu.

Executive Summary

Prior research has investigated whether diversification is beneficial for the VC industry. Managing VC investments is typically viewed as requiring highly specialized skills, knowledge, and time to select and assist investee companies. This suggests excessive diversification should come at a cost. Existing studies on whether diversified VC funds underperform specialized VC funds provide contradictory results, while recent studies tend to indicate a premium for diversified VC funds. This conclusion was recently attributed to knowledge-sharing effects across different industries and stages of development.

Understanding the impact of diversification versus specialization is particularly crucial for VC because fund managers aim to build a portfolio of promising firms and much of the value-adding may come from their capacity to actively assist investees and create synergies between them. In this paper, we explore an alternative explanation for the diversification premium based on risk effects from diversification to argue that diversification may lead to higher fund returns (which we call the "Risk Hypothesis"). We explore the joint interaction among risk, diversification, and performance. Greater diversification reduces fund risk, enabling risk-averse managers to select riskier investments in the first place and, thus, investments with higher expected returns. In this framework, greater diversification represents more investments in riskier ventures. However, the increased risk of individual ventures is compensated in part by greater diversification at the fund level. Ultimately, given the higher risk of each venture, the average return should be higher.

Our sample originates from the CEPRES database that includes detailed information of VC investments at the deal and fund levels, including cash flow data. We use an international sample of 308 VC funds that invested in 10,131 portfolio companies. We employ two measures of diversification: industry and stage of development. Our analysis indicates that greater industry

diversification leads to a higher fraction of funds invested in riskier, hi-tech ventures; similarly, greater stage diversification represents in our sample of VC funds a greater fraction of funds invested in early-stage ventures. Both represent increased investments in riskier ventures, consistent with underlying assumptions of the Risk Hypothesis.

Using multivariate analyses, we find that both dimensions of diversification (industry and stage of development) leads to higher return (measured by fund IRR), provided the VC fund is run by experienced managers. For less experienced VC funds, we find no relationship. Thus, these results support the idea that experienced VC fund managers who are able to access better deals benefit from diversifying in more industries and/or stages of development. We further find that diversification affects both types of risk, upside and downside risks. Overall, we conclude that our findings support the Risk Hypothesis. Finally, we find evidence for strong persistence in the level of diversification over time by VC firms, which suggests that part of the diversification strategy is determined by the accumulated expertise of VC managers. When managers diversify primarily into industries in which they lack experience, we show that greater industry diversification can even have a negative overall impact on fund performance. This study offers implications of how VC fund managers' investment decisions are influenced by strategic portfolio considerations, which in turn affect which innovative ventures receive funding.

1. **Introduction**

The question whether diversification is detrimental to venture capital (VC) has attracted a great deal of attention but is still under debate among entrepreneurship and finance scholars. Managing VC investments is viewed as requiring highly specialized skills, knowledge, and time to select and assist investee companies well (Dimov and De Clercq, 2006; Norton and Tenenbaum, 1993). This leads to a smaller number of investments (Bernile et al., 2007; Jackson et al., 2012; Kanniainen and Keuschnigg, 2003) or investments in a smaller set of industries (Cressy et al., 2007; Humphery-Jenner, 2013), which means that a discount (lower performance) rather than a premium for more diversified funds should be expected. Thus, managing VC investments in entrepreneurial firms is a strategic choice (generally described from the beginning in the private placement memorandum) that directly affects the type of ventures that will more easily receive capital.

While other studies have explored costs and benefits of diversification, the existence of such a diversification discount for VC funds (and private equity funds more generally) remains unclear. Humphery-Jenner (2013) documents a premium, which he explains by the enhanced knowledge-sharing capacity across more investments and reduced managerial risk aversion when the fund is more diversified. Other studies also document a positive relationship between fund diversification and performance (Humphery-Jenner, 2012; Knill, 2009; Lossen, 2009), though without testing specific economic channels of this relationship.[1]

In this paper, we explore an alternative, more direct explanation for the diversification premium based on endogenous risk effects from diversification. We investigate a cost-side factor of

[1] Other studies find a negative relationship (e.g., Dimov and De Clercq, 2006; Gompers et al., 2009; Han, 2009), or even a non-linear relationship (Matusik and Fitza, 2012; Yang et al., 2014). We discuss these studies and the differences in performance measures used in these different studies in Section 2.

fund specialization by arguing that specialization also increases expected managerial exposure to risk, which in turn affects the selection process of investments themselves. Thus, this paper is the first to jointly (1) assess the impact of diversification on fund performance and fund risk, while explicitly taking into account the asymmetric nature of VC returns, and (2) explore how deviations from past diversification experience of the VC firm affect the relationship among current diversification, performance, and risk. Thus, we examine to which extent expertise matters to explain these relationships.

Understanding the impact of diversification versus specialization is particularly crucial for VC because fund managers aim to build a portfolio of promising firms and much of the value-add may come from their capacity to actively assist investees and create synergies between them (Cressy et al., 2007; Humphery-Jenner, 2013; Norton and Tenenbaum, 1993). In the same vein, entrepreneurs want to receive funds from investors who devote enough time and have the right knowledge and skills to help add value. While the finance literature argues that risk reduction is a primary benefit of diversification (Markowitz, 1991), its impact on portfolio building in the context of active managers is particularly important in VC, given the significant investment risks involved in these types of investments (Cochrane, 2005; Cressy et al., 2014; Ewens et al., 2013). Much of the literature focuses on the relationship between diversification and performance without considering the simultaneous impact on fund risk.

In this study, we explore the interaction among risk, diversification, and performance. We expect a positive impact of diversification on fund performance as a result of a risk channel (which we call the "Risk Hypothesis"), in which greater diversification reduces fund risk, enabling risk-averse managers to select riskier investments in the first place and, thus, investments with higher expected returns. For example, it may induce VC managers with a stronger diversification strategy to invest more in early-stage ventures, which tend to be riskier than later-stage ventures. However, the increased risk from investing in more early-stage ventures is compensated in part by greater diversification. Ultimately, given the higher risk of each venture, the average return may eventually be higher (as ventures with the highest potential also entail higher risk). A similar outcome may result through a larger diversification across industries, as industries also vary greatly in terms of risk and return.[2] To test our Risk Hypothesis thoroughly, we explicitly control for the endogeneity of risk, as investment decisions fund managers make simultaneously affect diversification and risk and also performance. The Risk Hypothesis proposed and tested in this paper sheds light on the cost side of specialization when VC fund managers are risk averse. We further draw implications for entrepreneurs and entrepreneurship literature.

Understanding how diversification and the resulting risks relate to VC fund managers' investment decisions is crucial to gain insights into how they take into account portfolio perspectives in their decisions to provide funding to investees. Managers do not make investment decisions in isolation without any regard for the impact on the overall portfolio of investments. Ultimately, these decisions also affect the availability of capital to innovative start-ups. We therefore contribute to the entrepreneurship literature by offering a better understanding of how portfolio-level risk affects the selection process in VC, the provision of capital to risky start-ups, and its impact on performance. Our study complements the strand of literature on VC fund manager specialization (Cressy et al., 2014; Cressy et al., 2007; Ewens et al. 2013; Gompers et al., 2009; Humphery-Jenner, 2013; Jackson et al. 2012; Knill, 2009; Matusik and Fitza, 2012; Norton and

[2] As will become clear below, we use a large sample of VC funds to test this prediction. The claims made here with regards to what diversification means for risk are backed by our data. For instance, a greater stage diversification in our sample (which we measure by 1 – Herfindahl index of the stages of development in which the fund invested) is positively correlated with a greater fraction of funds invested in early-stage ventures. Similarly, greater industry diversification in our sample is correlated with a greater fraction of funds invested in hi-tech industries. Both, early-stage and hi-tech ventures, are considered riskier investments, consistent with the examples presented here.

Tenenbaum, 1993), which argues that investing in a narrower set of investment segments offers costs and benefits.

Existing studies do not test this risk-based channel directly, because they generally lack the proper data to measure risk. A sometimes used, indirect proxy for portfolio risk is the fraction on investments made in an early stage of development (Ruhnka and Young, 1991; Seppa and Laamanen, 2001); however, this proxy does not take into account that risk also varies across industries. In addition, to the best of our knowledge, while several studies document the importance of risk in VC, they do not explicitly control for the endogenous impact of risk on investment decisions of fund managers, leading to the implicit assumption that managers are risk neutral. Moreover, whereas existing studies often rely on indirect proxies of VC performance, such as the fraction of companies that went public or the growth of capital under management (e.g., Gompers et al., 2009; Knill, 2009; Matusik and Fitza, 2012), we are able to construct precise fund-level measures of returns (the fund internal rate of return [IRR] based on all the individual investments done by the fund) and risk (standard deviation of deal-level IRR of individual investments), based on a large, international deal-level sample. Our investment data stem from a proprietary dataset collected by Center of Private Equity Research (CEPRES), which offers detailed information on individual investments (including cash flows over time), the participating funds, and the fund managers.

We offer different results that support the Risk Hypothesis, while also leaving room for other hypotheses to hold simultaneously. We find that for experienced VC firms, both dimensions of diversification considered in our study (i.e., industry and stage of development) lead to higher returns (measured by fund IRR), consistent with the notion that diversification offers a premium on average. We find no relationship between diversification and performance for less experienced VC firms. A plausible explanation is that the more experienced VC firms are more likely to have access to a larger pool of investments opportunities, which helps them achieve a better mix of risk and return. However, when we control for ex ante (expected) fund risk, this relationship disappears, suggesting that the risk effect presented by the Risk Hypothesis is an important driver that links diversification, risk, and performance in VC funds. We further explore how diversification affects the ex post (realized) risk of VC funds. Because VC funds exhibit highly skewed returns, we consider the effects of diversification on both upside and downside risk. Finally, we document persistence in the diversification strategy of VC funds, and that accumulated expertise through previous funds is crucial to obtain higher performance from diversification.

Our analysis produces several important findings and implications that partly contrast earlier studies. For example, we find that after controlling for endogeneity, higher industry diversification leads to higher upside and downside risks. This finding also provides direct support for the Risk Hypothesis that the higher performance of more diversified funds is due to higher levels of risk taking. We also provide evidence that there is strong persistence in the level of diversification over time by VC firms, which suggests that part of the diversification strategy is also exogenously given by the accumulated expertise of VC managers. Because managing a VC investment requires detailed knowledge of the industry and stage of the portfolio company, we finally explore whether the effects of diversification on performance depend on whether managers diversify into areas in which they have gained experience. We find that the overall effect of industry diversification on fund performance depends on which industries managers choose for diversification. When managers diversify primarily into industries in which they lack experience, high industry diversification can even have a negative overall impact on fund performance. In contrast, we find that deviations from past investment stage experience do not significantly affect fund performance, which suggests that past industry experience is more important for fund performance than stage experience. These results may also help reconcile the mixed empirical evidence on performance and diversification from prior studies. For prior studies that rely on samples in which VC managers lack proper expertise in the areas of diversification, our results suggest a negative relationship between performance and (industry) diversification.

The remainder of this study is structured as follows: Section 2 presents a literature review and highlights our contribution. Section 3 describes our data and discusses our sample. Section 4 presents our results. Section 5 discusses extensions and robustness checks. Section 6 concludes by presenting implications for entrepreneurship literature.

2. Literature review and theory development

[Tighten the first FIVE paragraphs.] Questions about how entrepreneurial firms raise capital and how VC managers allocate funds to innovative start-ups are at the core of entrepreneurship research, given the difficulties for these start-ups to receive adequate funding (Berger and Udell, 1998; Cassar, 2004). In particular, early-stage ventures tend to experience the greatest difficulties in closing their funding gaps (Cressy, 2002). The interest in the question of diversification versus specialization in VC is not new, and it is well recognized that VC (and private equity more generally) fund managers are actively involved in their investments (see, e.g., Cressy et al., 2007; Gompers, 1995; Hellmann and Puri, 2002; Kang et al., 2011). Thus, an understanding of portfolio effects across different investments is crucial for both VC managers and entrepreneurs. The notion that VC fund managers are active investors is further evidenced by the typical limitation of portfolios in terms of number of investments (Bernile et al., 2007), potentially restricting the scope of diversification. This is because VC managers would otherwise devote less time and attention to each portfolio company when investing in more companies (Cumming, 2006; Cumming and Dai, 2011; Gifford, 1997; Jaaskelainen et al., 2006). Bernile et al. (2007) show that active fund managers face a tradeoff between larger portfolios and lower average company values. Although a larger portfolio does not imply greater industry or stage diversification (which we consider in this study, in contrast with Bernile et al. [2007], who consider the overall number of investments rather than the diversity of these investments), increasing diversification along at least one of these dimensions could force managers to monitor and focus on multiple investment stages and possibly on multiple industries rather than focusing on only a few investments or sectors. Thus, the overall fund returns are likely to be lower as diversification increases. The relative importance of these different effects is unclear however, and most studies generally abstract from risk-reduction effects of diversification.

Instead, many studies focus on benefits associated with specialization, such as information sharing between investments (Norton and Tenenbaum, 1993) and organizational improvements (Gompers et al., 2009). As a result, this strand of literature often concludes that specialist funds outperform diversified funds (i.e., generalists). In contrast, Humphery-Jenner (2013) concludes that diversification increases fund returns because of knowledge sharing and learning across investments. Other studies conclude the same. For example, Knill (2009) finds that more diversified managers raise subsequently more follow-up capital, suggesting that diversification also leads to higher performance because realized performance enables fund managers to raise more capital in the future. In a different test, Humphery-Jenner (2012) documents a positive relationship between industry and geographical diversification and performance. Matusik and Fitza (2012) find a U-shaped relationship in which the effect is first negative and then becomes positive. Performance is lowest for intermediate levels of diversification. They develop a framework of costs and benefits of diversification based on knowledge resource diversification, flexibility, and environmental uncertainty. Yang et al. (2014) also find a U-shaped relationship in the specific case of corporate VC.

In contrast, Cressy et al. (2014) find that industry diversification reduces fund performance but that geographical diversification improves performance.

Our contribution is to explore the impact of expected risk exposure on the selection of investments that may be at play at the same time as the channels discussed previously. Risk effects matter when VC managers are risk averse because they are no longer indifferent to the overall risk level of their fund. Moreover, VC fund managers have increased incentive to manage the risk level of their portfolio companies through diversification, because their compensation is based on performance (carried interest). Typically, VC funds invest in risky portfolio companies, which have highly skewed returns with significant bankruptcy risk (Cochrane, 2005; Gompers and Lerner, 1998; Korteweg and Sorensen, 2010). Therefore, risk reduction is important for VC fund managers. In practice, they are able to affect their risk exposure by choosing an appropriate set of industries (which also have their own level of risk) or development stages of ventures. For example, expected risk exposure is likely higher when allocating a larger fraction of funds to early-stage ventures. In practice, by selecting investments, fund managers set ex ante the degree of diversification, the expected risk and expected return of the fund. At the end of the fund's lifecycle, this leads to realized fund risk (dispersion of returns of individual investments) and fund return, which we are able to measure with our data.

The Risk Hypothesis explored in this study states that risk-averse fund managers who diversify investments more (in either more industries or stages of development) may invest in riskier and, thus, potentially more profitable companies, because diversification eliminates some of the deal-level risk. In contrast, specialists may prefer less risky companies as a way to limit overall risk exposure, at the expense of higher performance.[3] For diversified funds, the higher fund returns stem from the fact that diversified funds invest in startups with higher risk and thereby also higher return prospects. This is typically the case for early-stage ventures as opposed to later-stage ventures, or when a larger fraction of funds are invested in riskier industries but with higher prospects. Crucially, this notion of diversification is not directly related to the number of ventures, which affects the amount of time that VC fund managers can devote to each venture. Rather, our analysis focuses on the composition of the portfolio itself.

We further expect the effect on performance to be strongest for more experienced and knowledgeable VC fund managers, because they are more likely to have access to a larger pool of investment opportunities that allow them to build a portfolio more easily with an optimal risk–return exposure than less experienced managers. Therefore, expertise is likely to be a critical ingredient to enable VC fund managers to source promising deals in a larger range of industries or stages of development. Also, experienced and knowledgeable managers are more likely to be invited to join syndicates that allow them to more easily diversify across industries and stages of development. In terms of the impact on risk, we develop the Risk Hypothesis separately for industry and stage diversification, because industry diversification does not occur in the same way as stage diversification. If a VC manager diversifies more across industries, the fund will carry less industry-specific risk, thus enabling the manager to engage in riskier portfolio companies (i.e., portfolio companies with a high downside risk but also a high upside potential in terms of returns).[4] We therefore expect that higher industry diversification leads to higher downside risk of a fund but also

[3] Humphery-Jenner (2013) discusses this economic channel as a possible alternative explanation for the documented results on the effect of diversification on performance. However, he does not investigate it because of a lack of data on risk.

[4] We formally define the concepts of downside and upside risk in the next section, in which we show the exact formula. Upside risk is generated by high volatility of returns on the upside (i.e., through very high returns); thus, upside risk is deemed "good" risk. In contrast, downside risk is "bad" risk, because it captures volatility of losses (negative returns).

higher upside risk (which is due to very high returns). Because higher risk taking should go along with higher expected returns when VC investments are properly priced, this also leads to a positive relationship between industry diversification and ex post performance. We further expect that diversification across stages has a slightly different impact on fund downside and upside risk than industry diversification. In VC financing, different investment stages have very different risk and return profiles. Early-stage investments, such as investments in seed or start-up companies, are associated with higher levels of downside risk and higher upside potential, whereas later-stage investments are associated with lower downside risk and moderate upside potential (and, thus, also less upside risk). By diversifying into later stages, fund managers can limit the downside risk of the fund. The lower downside risk in turn enables them to simultaneously engage in riskier early-stage portfolio companies, which enhances the fund's expected returns. Similarly, stage diversification may result from stage financing. Staging enables sorting out bad investments more quickly so that returns are higher and losses are reduced (which means less downside risk). Good investments receive further capital to fund follow-up development stages. We therefore expect that the higher performance of funds that diversify more across investment stages goes along with lower downside and higher upside risk. We test these predictions subsequently.

3. **Data and summary statistics**

3.1 Data

We use a research dataset provided by CEPRES. A unique feature of the data is that they provide detailed information, including cash flow data at the deal and fund levels; other commonly used databases tend to provide data at either the fund level or the deal level only. Several studies have used the database, including Cumming, Schmidt, and Walz (2010), Cumming and Walz (2010), Franzoni, Nowak, and Phalippou (2012), and Krohmer, Lauterbach, and Calanog (2009).

CEPRES obtains data from private equity (VC and buyout) firms that participate in a general partner network (called Private Equity Analyzer). Private equity firms that participate in this network report monthly cash flows and investment details (e.g., industry, investment stage) for each deal and fund in which they are involved. In exchange, they receive statistics, such as risk-adjusted performance measures, for their own investments and for the aggregate private equity market. CEPRES effectively anonymizes all the information to meet the confidentiality requirements of the VC and buyout firms that provide data to CEPRES. This means that third parties are not able to identify individual portfolio companies, funds, or management firms. This eliminates the incentives for management firms to overstate the results they report to CEPRES. Lack of anonymity in other databases may result in overstating, partial reporting, or back-filling of information, amounting to positive self-reporting biases. In addition, CEPRES independently checks all reported data for accuracy and impartiality. For example, they independently check whether the reported fund-level cash flows are consistent with the reported deal-level cash flows. Additionally, CEPRES compares the information provided by the private equity firms on the funds and portfolio companies with information available from other commercial databases such as PREQIN.

The total database as of March 2011 includes information for 1,314 funds that have invested in more than 30,000 portfolio companies worldwide. It is important to note that these figures correspond to the full universe of private equity investing covered by CEPRES which includes the VC, buyout, and mezzanine segments. Out of these 1,314 funds, a total number of 442 funds have a self-designated focus on VC investments while the remaining funds focus either on buyout investments (567 funds), mezzanine investments (225 funds), or invest in all segments of the private equity universe (80 funds). For our study, we focus on the subset of the 442 VC funds. We apply several criteria to obtain our final sample. First, we only include funds in our sample which are fully realized or which are at least seven years old. This decreases the sample from 442 funds to 309 funds. Second, we exclude funds with vintage years prior to 1980 since the coverage of the CEPRES data is relatively poor in the 1970s. Excluding one fund with vintage year 1972 gives our final sample of 308 VC funds which have invested in 10,131 portfolio companies. Since CEPRES only includes funds in the database which provide complete data for all portfolio company investments of the fund, we did not have to exclude funds from our sample because of missing information.

In terms of data representativeness, a comparison of the number of sample funds with that contained in other commercial and proprietary databases commonly used in private equity research is worthwhile. The proprietary database Robinson and Sensoy (2016) use contains 292 VC funds, which is slightly less than our sample size of 308 VC funds. The commercially available private equity databases most often used in recent academic research on fund performance are BURGISS and PREQIN. For these databases, Harris et al. (2014) report sample sizes of 555 and 830 VC funds, respectively. Compared with BURGISS or PREQIN, our sample contains a lower but still sufficient coverage of VC funds. Importantly, the strength of the CEPRES dataset is its provision of detailed information on both the fund and deal level, whereas the mentioned data sources only provide fund-level information. This feature is crucial for our subsequent analysis because it enables us to calculate precise measures of fund diversification and risk.

3.2 Summary statistics

Table 1 (Panel A) reports the sample statistics for all the variables by mean, median, standard deviation, minimum, and maximum values. The average IRR in our sample of funds is 35.5%, with a median of 19.6%. Note that these performance figures are reported gross of management fees and carried interest payments and therefore do not represent the returns earned by the fund investors. The fact that the mean is higher than the median indicates that the distribution of returns is highly positively skewed, which is a common feature of VC returns (see Cochrane, 2005). The large standard deviation further implies a large dispersion of fund returns, as can also be inferred by comparing the minimum and maximum values, which amount to –30.6% and 476.70%, respectively.

Potential sample selection biases are a natural concern in private equity research. To assess potential bias, we can compare the IRR statistics of our sample with those of other databases used in the literature. PREQIN reports an annual average IRR of 24.9% for VC funds with the same vintage years as in our sample. Harris et al. (2014) report an average annual performance for VC funds of 12.8% for funds with vintage years in the 1980s, of 35.2% for funds with vintage years in the 1990s, and of –1.0% for funds with vintage years in the 2000s. Given the distribution of our sample funds by vintage years, this yields an average comparable annual IRR of their data of 22.5%. These figures are substantially lower than the average annual IRR of 35.5% of our sample VC funds. However, it is important to note that CEPRES reports performance before all fund-level fees while the PREQIN database and the data Harris et al. (2014) use is reported net of all fund-level fees. Private equity fund managers typically receive a fixed annual management fee and a performance-based incentive fee, also known as carried interest. According to Robinson and Sensoy (2013), the median VC fund has an annual management fee of 2.5% and a carried interest of 20%, with an annual hurdle rate of 8%. Using this typical compensation structure, we perform a simple back-of-the-envelope calculation to convert our average sample performance before fees into performance after fees. Overall, this calculation reduces the annual average IRR of our sample funds to 27.1%

after fees,[5] which is still slightly higher but close to the 24.9% from PREQIN and the 22.5% from Harris et al. (2014). Thus, we conclude that a significant selection bias is not a factor in our sample. Finally, it is also important to note that our cross-sectional analyses would only be sensitive to selection issues insofar as any potential bias in the data is correlated in specific ways with the explanatory variables.

We consider two diversification measures, one along the industry dimension (labeled *Industry Diversification*) and one along the different stages of development (*Stage Diversification*) of the portfolio companies in which the VC fund invested. We measure the first by 1 – Herfindahl index of the industries and the second by 1 – Herfindahl index of the different stages of development (see Table 1 for more details on the different categories considered).[6] The mean (median) figures of our diversification variables are 0.657 (0.730) for *Industry Diversification* and 0.466 (0.550) for *Stage Diversification*. These values cannot be directly compared across the two dimensions, because some of these differences are likely to be attributed to the different number of categories considered for each dimension. Seventy percent of our sample contains US funds, which is consistent with the common notion that the United States is the dominant market for VC investments worldwide. The average fund in our sample invests in 32.893 portfolio companies and has 22.668 investment professionals, leading to an average value of 1.45 companies managed per investment professional. The VC management firms in our sample are mature, as indicated by *Firm*

[5] This simple approximation assumes a typical fund lifetime of 10 years and that committed capital is steadily and fully invested over the entire lifetime. Let $\overline{IRR}$ denote the average IRR before fees, f the annual management fee, c the carried interest level, h the hurdle rate, and T the lifetime of the fund. The reduction in IRR caused by management fees can be approximated by $\Delta IRR_{fee} = \overline{IRR} - \left[(1-fT)^{1/T}(1+\overline{IRR})-1\right]$, and the reduction in IRR caused by carried interest payments can be approximated by $\Delta IRR_{carry} = (\overline{IRR} - \Delta IRR_{fee} - h)c$.

[6] This measure of diversification (or specialization) is also used in other venture capital studies, including Cressy et al. (2014), Dimov and De Clercq (2006), Gompers et al. (2009), Jaaskelainen et al. (2006), and Yang et al. (2014).

Age (mean of 18.001 years), and participate, on average, in 3.887 rounds in their portfolio companies.

[Table 1 about here]

Table 1 also shows statistics for our risk measures. We use upside and downside volatility as measures for investment risk of a fund as a way to disentangle "good" from "bad" fund risk. Using volatility seems unconventional under the standard asset pricing theory, which suggests that only systematic risk is priced in equilibrium. However, in contrast with this conventional view, Ewens et al. (2013) provide evidence that idiosyncratic risk is also a priced factor for VC and private equity investments. They develop a theoretical model to analyze the role of idiosyncratic risk in the pricing of VC and private equity investments. Their model predicts a positive relationship between the investment returns of funds and the ex post idiosyncratic risk of the funds' returns. Empirically, they find a strong correlation between realized total risk and fund returns. This evidence suggests that total risk as measured by volatility is an appropriate risk measure for VC and private equity funds. Note that we use upside and downside volatility rather than total volatility in this study. We do so because VC investments typically involve highly skewed investment returns that deviate substantially from a normal distribution, as discussed previously. An important drawback of the standard return volatility is that it treats positive and negative deviations from the mean return as equally undesirable risk. Tobin (1958) shows that volatility can be the risk measure of choice only for normally distributed returns. In contrast, downside volatility is a risk measure that accounts for asymmetric return distributions by considering only negative deviations from a pre-specified target return. Markowitz (1991) was the first to propose the concept of downside volatility; he argues that downside volatility is a more plausible measure of risk than standard volatility because investors worry about under-performance rather than over-performance. However, downside risk is meaningful not only from an individual investor's perspective but also from an asset pricing perspective. For example, Bali et al. (2009) demonstrate a strong risk–return tradeoff using downside risk measures.

In this paper, we also consider upside volatility, which is a measure of the upside potential (the "good" risk) of the returns of a VC fund. In contrast with downside volatility, upside volatility considers only positive deviations from a pre-specified target return. This additional measure allows us to further assess how diversification affects the right tail of the return distribution. In other words, does diversification affect the possibility of a VC firm generating higher returns? For example, a negative relationship between diversification and the upside volatility suggests that diversified funds have limited access to very high returns. Because time series of investment returns are not available for private equity funds, we proxy upside and downside volatility of a fund by using the IRRs of the portfolio companies in which the fund has invested. For a fund that has invested in N portfolio companies with returns given by IRR_1, IRR_2, …, IRR_N, we can calculate the downside volatility by

$$\sigma_{Down} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\min\left(IRR_i - Tar, 0\right)\right]^2} \qquad (1)$$

and the upside volatility by

$$\sigma_{Up} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\max\left(IRR_i - Tar, 0\right)\right]^2}\ . \qquad (2)$$

In both equations, *Tar* denotes the return target. Motivated by Ang et al. (2006), we use a target return of zero in all the following calculations.

Panel A of Table 1 shows that the average upside volatility of the sample funds is much larger than the average downside volatility. This difference also indicates that the returns of our sample funds are highly positively skewed and deviate substantially from a normal distribution, which is consistent with the distribution of VC returns.

Panel B of Table 1 shows the correlation matrix of these same variables. As is evident, multicollinearity is not a major issue given the lack of excessive correlations between the explanatory variables.

4. **Analysis and results**

Given that diversification affects the risk of VC funds, we examine whether fund managers invest in riskier deals to achieve higher returns. If so, this would lead to a positive relationship between fund diversification and fund performance, consistent with our Risk Hypothesis. Humphery-Jenner (2013) finds that higher diversification across industries leads to higher returns as measured by funds' IRR, proposing a hypothesis based on learning. We aim to explore a cost-side factor, which stipulates that the positive relationship between diversification and fund IRR is also related to fund-level risk.

4.1. Main results on the risk hypothesis

To test the Risk Hypothesis, we perform several analyses. As a first step, we examine the relationship between IRR and diversification (i.e., Equation 3), followed by fund risk and diversification (Equation 4). Both left-hand-side variables are outcome (ex post) variables and determined jointly at the end of the fund's lifetime, while diversification pertains to the portfolios selected during the first years of the fund's lifetime (the so-called investment period of the fund):

$$IRR_{i,t} = \alpha + \beta_j Diversification + \beta_i X + \varepsilon \text{ and} \qquad (3)$$

$$FundRisk_{i,t} = \alpha + \beta_j Diversification + \beta_i X + \varepsilon \ , \tag{4}$$

where *IRR* is the fund's realized internal rate of returns, *Diversification* is either *Industry Diversification* or *Stage Diversification*, *Fund Risk* is either the upside or downside fund volatility of the realized IRR, and *X* are control variables, which include fund origin (US versus non-US), the number of portfolio companies in the fund, number of professionals in the fund, fund size, average number of investment rounds, and average size of investments. All these variables are defined in Table 1. These specifications also include fund (vintage) year dummies. A positive and significant β_j in Equation (3) suggests that diversification increases performance, consistent with Humphery-Jenner's (2013) study. A positive and significant β_j in Equation (4) suggests that diversification also increases fund risk, in which the impact on downside risk ("bad" risk) is particularly crucial for our Risk Hypothesis. The analysis of upside risk complements the picture, as it allows us to examine whether diversification also affects the likelihood of generating very high returns. The distinction between upside and downside risk offers insights into differential effects for stage and industry diversification, as we show subsequently.

Crucially, risk is not a mediating factor in our model (Aguinis et al., 2016) but rather an outcome variable in our analysis. This is because we use realized risk just like realized returns. The risk we consider in the context of strategic choice of diversification is ex ante risk, which is not directly measurable (though we include some proxies for ex ante risk subsequently). An important but common assumption in finance (Markowitz, 1991) is that ex ante and ex post risk are correlated.

Table 2 reports the results of Equations (3) and (4). Models 1 and 2 show that a one-standard deviation change in diversification increases the returns by 3.774% (= 0.222*17.0%) using the industry Herfindahl index and 3.260% (= 0.247*13.2%) using the stages Herfindahl index. The evidence is statistically significant at the 1% level for stages of development but only 10% for industries. Thus, overall, we find a positive and statistically significant relationship between diversification and performance (i.e., more specialized funds underperform on average), though mainly for stage diversification.[7] These values of impact are also economically meaningful. In Models 3–6, we estimate Equation (4) for upside volatility (Models 3 and 4) and downside volatility (Models 5 and 6) to offer first insights into the Risk Hypothesis. We find a positive and significant relationship between industry diversification and downside volatility (i.e., higher industry diversification increases the likelihood of picking "losers"). This result is surprising from a general finance perspective because it counters the general notion that higher diversification decreases downside risk. The positive coefficient for upside volatility further suggests that higher industry diversification also increases the likelihood of picking "stars." However, this evidence is only weakly significant at the 10% level. For stage diversification, we find a weak (10% significance level only) and negative relationship to downside volatility and no significant relationship to upside volatility. This implies that stage diversification does not affect the upside potential in fund returns but can reduce the likelihood of picking underperforming deals.

[Table 2 about here]

Taken together, these results offer a consistent picture of higher risk and higher return for industry diversification but especially more downside volatility ("bad" risk) in the event of industry diversification with weak compensation in terms of IRR. Thus, the findings suggest that the extra returns that could be achieved through higher industry diversification mainly represent a compensation for the higher levels of risk taken. Stage diversification suggests a somewhat

[7] We also examined whether diversification increases the probability of achieving a top-quartile performance, using a logit model. We obtained non-significant results. In addition, we checked for the impact of outliers by winsorizing IRRs at the 1% and 5% levels. In both cases, we obtain similar results as reported in the text.

different picture. It increases returns significantly and weakly reduces downside volatility ("bad" risk). These findings are consistent with stage diversification being quality driven, possibly because of stage financing. Staging enables sorting out bad investments more quickly so that returns are higher and losses are reduced (which means less downside volatility). Overall, these results offer empirical support for the Risk Hypothesis that the positive relationship between IRR and diversification is driven by differences in risk taking. For industry diversification, our results suggest that higher diversification is accompanied by higher downside (i.e., "bad") risk and higher upside (i.e., "good") risk. In case of stage diversification, the results suggest that higher diversification is accompanied by lower downside risk.[8]

The specifications in Table 2 includes several control variables, one of which is the number of portfolio companies included in the VC fund (the variable *Portfolio Companies*). This variable allows controlling for the fact that the number of portfolio companies may affect our diversification measures. Although they are based on the fractions of funds invested and not the absolute number of companies in the portfolio, a larger portfolio may still force the VC manager to invest in a larger set of industries or stages of development. This may affect the amount of time available for each investee company. Consistent with theories on limited attention (Cumming, 2006; Cumming and Dai, 2011; Gifford, 1997; Jaaskelainen et al., 2006), we expect a negative impact on fund performance. Our results generally support this prediction.

We also argued in Section 2 that the effects are strongest for the most experienced VC firms, because these firms are better able to attract more investment opportunities and thus can more easily achieve their desired portfolio selection outcome from a larger pool, which in turn helps

[8] In unreported analyses, we considered geographical diversification by calculating a measure similar to the other two dimensions (based on the Herfindahl index) but with the 86 different countries represented in our sample. We found no impact of geographical diversification on either performance or risk.

achieve diversification. Moreover, more experienced VC firms are likely to have accumulated more expertise, so they can more easily invest in a larger range of industries and stages of development and thereby mitigate downside risk. To test this extra prediction, we run the same specifications (Equations (3) and (4)) using an interaction term between the diversification measure and a proxy for VC firm experience. For the latter, we use two measures, one based on VC firm age (i.e., whether the fund belongs to a VC firm with *Firm Age* larger than the sample median) and one based on investment experience (i.e., whether the fund belongs to a VC firm with a value of *Past Portfolio Companies* larger than the sample median, meaning the firm has accumulated extensive experience through a large number of past investments with other VC funds).

Table 3 reports the results. Panel A shows the results for the experienced VC firms using *Firm Age*, and Panel B shows the results using *Past Portfolio Companies*. We find that experienced VC firms benefit most from diversification in terms of returns while less experienced firms do not. The higher returns of experienced VC firms are associated with more upside volatility for stage diversification (the "good" risk, consistent with the presence of high-performing investees in the portfolio) and no significant impact on downside volatility. For industry diversification, we obtain similar results to the full sample, in that higher performance comes with higher downside risk, but not more than less experienced VC firms. In contrast, less experienced VC firms generate no extra returns from diversification, while stage diversification even reduces their upside volatility (i.e., their capacity to invest in outperforming start-ups), and industry diversification increases the downside volatility. In Panel B, we use the second measure of VC experience and find consistent results, though the significance level sometimes varies. Overall, the results show that the simultaneous impact on fund risk helps explain the positive relationship between IRR and diversification, and the results are strongest for the most experienced VC firms. This finding is consistent with the Risk Hypothesis and serves as a first piece of evidence for the hypothesis. Given the possibility of endogeneity however, we consider this first empirical evidence preliminary.

[Table 3 about here]

As an extended test, we now include ex ante measures of risk in Equation (3). If risk helps explain the relationship between diversification and performance, we expect the coefficient of the diversification measure to be reduced or even lose statistical significance when these measures are included. To avoid endogeneity problems, we calculate our ex ante measures of fund risk using a qualitatively similar approach to that proposed by Phalippou (2010). This approach uses historical data rather than realized IRRs of the fund (which can only be calculated ex post, as done in Equations (1) and (2)). We again consider ex ante downside volatility and ex ante upside volatility. Formally, *Downside Vol Ex Ante* is the downside volatility of all portfolio companies managed by the same VC firm before raising the current fund, while *Upside Vol Ex Ante* is the upside volatility of all portfolio companies managed by the same VC firm before raising the current fund. These ex ante measures of risk better capture what the market expects for the risk of the current fund. Given that the market lacks better information when the fund is set up, we assume here that the market's expectation stems from the risk the VC manager has taken in the past.[9]

Table 4 reports the results. Models 1 and 2 again show the standard performance regressions using our measures of industry and stage diversification; they are identical to Models 1 and 2 in Table 2 and serve as comparisons. In Models 3 and 4, we include our ex ante downside and upside risk measures as additional control variables to directly test the Risk Hypothesis. In line with

[9] As alternative measure of ex ante risk, we considered a dummy variable equal to 1 if the fund's focus is on early-stage companies (see Ruhnka and Young, 1991; Seppa and Laamanen, 2001). However, this alternative measure does not explain ex post performance. The inclusion of this extra control variable as a proxy of fund focus also does not affect our main conclusions. Similarly, our conclusions remain unchanged when we proxy fund ex ante risk by the fraction of early-stage investments made by the fund.

finance theory, we find that the coefficient on *Downside Vol Ex Ante* is positive and significant (at the 5% level), which implies that a higher level of downside risk increases fund performance. The coefficient on *Upside Vol Ex Ante* is close to zero and statistically non-significant in all specifications. More important, Models 3 and 4 show that the positive relationship between IRR and diversification turns non-significant when controlling for fund risk. These results support the Risk Hypothesis that differences in ex ante fund risk drive the relationship between IRR and diversification. As our sample includes US and non-US funds, we also examine whether the sub-sample of US funds drives the regression results. Models 5 and 6 include a dummy variable that takes the value of 1 for the US funds and 0 otherwise. We find that including the US dummy decreases the significance of the coefficient on *Downside Vol Ex Ante*. This result is most likely due to the higher levels of risk US funds take. However, our main result that the coefficients on the diversification measures turn non-significant continues to hold when we include the US dummy as an additional control variable.

[Table 4 about here]

As a robustness check, we further examine the impact of activeness of VC managers by adding the constructed measures to our performance regressions to determine whether it explains performance. We use two measures of "activeness": (1) a dummy variable that takes the value of 1 if the fraction of investments in which the VC manager holds a board seat is above the median (third quartile) of all funds in our sample and 0 otherwise and (2) the fraction of the portfolio companies in which the VC fund holds a board seat. We find that the level of activeness of a VC fund only has a significant, positive impact on fund performance for the most active VC firms (results not reported in tables, but available on request). More important, the results show that the level of activeness of a VC fund does not explain the positive relationship between diversification and performance, as our measures of diversification remain at the same significance levels after controlling for activeness.[10]

4.2 Endogeneity

Campa and Kedia (2002) document self-selection and endogeneity issues related to diversification choices. They focus on whether the negative relationship between firm value and diversification is due to endogeneity. However, in the context of the Risk Hypothesis and owing to the nature of VC investments (see Humphery-Jenner, 2013), the potential endogeneity arises among risk, performance, and diversification. For example, VC fund managers may decide to invest in riskier start-ups while diversifying more across industries or stages of development as a way to reduce overall risk. If so, this would suggest that fund risk and diversification are jointly determined. The same holds for fund returns. To address this concern empirically, we use the Generalized Method of Moments (GMM) instrumental variable estimation approach, in which VC firm experience (proxied by *Firm Age*) serves as an instrument for the *Stage* and *Industry Diversification* measures. However, if endogeneity does not drive the relationship among risk, return, and diversification, the results reported in Table 2 remain valid. The following stages outline our method for controlling for endogeneity:

Stage I: We estimate diversification using Equation (5) as a function of different control variables and the instrument:

$$Diversification_{i,t} = \alpha + \beta_i X + \varepsilon \, , \tag{5}$$

[10] In an unreported analysis, we examine the combined effects of portfolio size and our measures of portfolio diversification on fund returns. Our results suggest that VC funds who also invest in a large number of portfolio companies will experience lower returns from increased stage diversification. This relationship is most likely driven by the fact that investments in early-stage companies require a high level of VC involvement. Thus, funds following a strong stage diversification strategy should limit the number of portfolio companies in which they invest. In contrast, we find no significant effect of the interaction between portfolio size and industry diversification on fund returns.

where *Diversification* is either the *Stage* or *Industry Diversification* measure and *X* includes the number of professionals, fund size, number of rounds, and average size of the fund investments. Our instrument is *Firm Age*, which is a proxy for VC firm experience, consistent with previous studies (e.g., Lee and Wahal, 2004). The choice of this instrument is motivated by the idea that more experienced management firms are better able to affect portfolio composition because of better access to high-quality deal flow than less experienced VC firms. This view is consistent with our findings in Table 3.

Stage II: We model the endogeneity among risk, return, and diversification using Equations (6) and (7):

$$IRR_{i,t} = \alpha + \beta_j Diversification + \beta_i X + \varepsilon \text{ and} \tag{6}$$

$$FundRisk_{i,t} = \alpha + \beta_j Diversification + \beta_i X + \varepsilon \text{ ,} \tag{7}$$

where *IRR* is the fund's internal rate of returns, *Fund Risk* is either the upside or downside fund volatility, *Diversification* is estimated in the first step using Equation (5), and *X* are control variables similar to Equation (5) but excluding our instrument. We estimate both steps simultaneously using GMM.

Consistent with previous studies (see, e.g., Humphery-Jenner, 2013), we use three diagnostic tests for the GMM assumptions: (1) Hansen j-test for over-identification of our instrumental variable, (2) Relevance test to assess whether excluding the instrument from Stage II is valid, and (3) Exclusion Criteria, where we assess the orthogonality of the instrument to the error term. Failure to reject the null hypothesis in the Hansen j-test suggests that the instrument is over-identified and thus consistent with the GMM assumptions. Rejecting the null hypothesis in the case of the Relevance test indicates that excluding the instrument from Stage II is consistent. The null hypothesis under the Exclusion Criteria test suggests that the instrumental variable is orthogonal to the error term.

Table 5 shows the Stage II results for industry and stage diversification using GMM estimations. For brevity, the Stage I results are not reported. Model 1 shows that industry diversification (our instrumented variable) continues to have a positive impact on the realized IRR, but its impact is significant only at the 10% level (as before). Similarly, Models 2 and 3 show that industry diversification has an equally positive impact on both upside and downside fund risk, again consistent with our results in Table 2; however, significance levels have become stronger. Our endogeneity test is based on the Hansen j-test, and our values range between 1.871 and 4.408, which are all lower than the critical values. For the Relevance test, we obtain Wald statistics values that are higher than the critical values, suggesting that we reject the null hypotheses that VC firm experience is a weak instrument in our GMM model. Finally, we examine whether excluding our instrument from Stage II is a valid assumption. Following the Exclusion Criteria test, we conclude that exclusion of the instrumental variable is relevant because the null hypothesis is not rejected at any conventional level. Although there is no perfect approach to ensure validity of instruments, our case offers some assurance that the results are qualitatively consistent with those when omitting the instrument.

In Models 4-6, we show similar results for our *Stage Diversification* measure instead of *Industry Diversification* measure to assess the robustness of the results obtained in Table 2. We also show similar endogeneity test results (Hansen j-test, Relevance test, and Exclusion Criteria test). *Stage Diversification* increases the returns and upside volatility but reduces downside volatility. While the coefficient signs of *Stage Diversification* remain the same, the results are now significant for both types of risk. Thus, *Stage Diversification* increases upside potential and, at the same time, reduces risk of incurring great losses (affecting downside volatility), generating superior benefits for *Stage Diversification*. Although we already established this finding in Section 4.1, it is even stronger when we control for the endogenous nature of VC managers' diversification decisions. Furthermore, the diagnostic tests indicate that the GMM model is correctly specified.

[Table 5 about here]

Overall, the results indicate that *Industry Diversification* is related to risk in a way that counters basic intuitions of finance theory. Basic finance theory suggests that high levels of diversification decrease both upside and downside risks. In contrast, we find that *Industry Diversification* leads to higher upside and downside volatility. This finding again corroborates the Risk Hypothesis that the higher performance of more diversified funds is due to higher levels of risk taking, which increases both the downside and upside potential in fund returns. Moreover, these results reinforce our previous conclusions (Table 2) because they remain valid even after we control for possible endogeneity of diversification choices.

5. **Persistence in diversification strategy and impact of past experience**

We perform several extensions to offer further insights into the results obtained. First, we examine persistence in industry and stage diversification to explore the question of whether the past diversification strategy of a VC fund manager is significantly related to the diversification strategy of the current fund. And second, we explore whether accumulated experience in terms of diversification is crucial in achieving the improved performance and reduced risk documented so far.

5.1 Persistence in diversification strategies

Investigating diversification persistence addresses the question whether VC managers pursue similar diversification strategies over time. Persistence in diversification would suggest that diversification is a matter of knowledge accumulation and not only driven by risk mitigation as shown so far. As discussed in Section 2, expertise is likely to be a crucial ingredient for VC fund managers to make advised investment decisions across a larger range of industries or stages of development.

Finding persistence in diversification strategies is a first step towards supporting the underlying assumption that accumulating knowledge matters in VC. Table 6 reports the results. The dependent variable in Models 1 and 2 is the industry diversification of the current fund, while the dependent variable in Models 3 and 4 is the stage diversification of the current fund. The explanatory variable *Industry Diversification (Previous)* is the industry diversification calculated for all previously managed VC funds of the same VC firm; similarly, the explanatory variable *Stage Diversification (Previous)* is the investment stage diversification calculated for all previously managed VC funds of the same VC firm. Model 1 shows strong persistence in industry diversification. The coefficient on *Industry Diversification (Previous)* is positive and strongly significant at the 1% level; the point estimate is 0.864, with a t-value of 20.57. The coefficient implies that a 10% higher past industry diversification is associated with an 8.64% higher industry diversification in the current fund. Model 2 supports the view that the evidence for persistence in industry diversification is robust when controlling for VC firm age, fund size, and number of professionals in the VC firm. Similarly, Model 3 shows a strong and positive persistence in stage diversification. This persistence is also highly significant at the 1% level. Again, this result remains robust when we control for VC firm age, fund size, and number of professionals (see Model 4). Overall, these results suggest that there is strong persistence in industry and stage diversification; that is, VC managers who have diversified a great deal over industries or stages in the past also tend to do so in their next fund. The most likely explanation for this behavior is that managers learn from their past investments and that changing the diversification strategy might involve significant costs for the manager or require substantial time.

[Table 6 about here]

5.2 Impact of past experience on performance and risk

Although that past diversification is a main determinant of the diversification level of the current fund (see Table 6), it does not answer the question whether managers tend to diversify into industries (stages) in their current fund for which they have gained experience or whether they tend to go to completely different industries (stages). For example, a VC manager who first manages a specialized biotech fund and then a specialized Internet fund would keep the same level of specialization (based on our measures of diversification) but is clearly investing in very different industries. Because managing a VC investment requires detailed knowledge of the industry and stage of the portfolio company, as discussed in Section 2, we would expect that managers primarily diversify into industries and stages in which they have acquired experience. To explore this question, we calculate Euclidian distances between the proportions the manager has invested in each industry (stage) in the past and the proportions the manager invests in the same industries (stages) in the current fund. Formally, we define the Euclidian distance measure as

$$\text{Euclidian} = \sqrt{\sum_{i=1}^{N}\left(w_i - w_{p,i}\right)^2}\ , \qquad (8)$$

where N is the number of different industries (stages), w_i is the proportion the manager invests in industry (stage) i in the current fund, and $w_{p,i}$ is the proportion the manager invests in industry (stage) i in all previously managed VC funds.

This measure is equal to 0 if the manager exactly invests the same proportion in each industry (stage) as in the past. Positive values of the measure indicate that the manager deviates from what was done in the past, and the deviation increases as the value becomes larger. The maximum value of the measure equals $\sqrt{N}$ and is attained in case the manager chooses completely different industries (stages) from those invested in the past.

The mean (median) value of the Euclidian distance for industry in our sample is 0.33 (0.32), which is relatively low for this measure. Given that there are 22 different industries in total, the mean value suggests that the average absolute deviation of the proportion in each industry, $|w_i - w_{p,i}|$, equals only $0.33/\sqrt{N}$=7%. The mean (median) value of the Euclidian distance for stage of development in our sample is 0.30 (0.24). The mean value here suggests that the average absolute deviation of the proportion in each stage equals 11.34%. This number is slightly higher than the average absolute deviation for the industries. Overall, this result provides some evidence that managers do take into account their past industry experience when choosing where to diversify in their current fund. They also consider past investment stage experience, but to a lesser extent.

It is important to analyze whether diversification differently affects fund performance when managers diversify into industries (stages) in which they have extensive past experience or whether they diversify into industries (stages) in which they have little or no past experience. We analyze this question in Table 7, which shows regression results that also explain the impact of the Euclidian distance measures on fund performance. Model 1 includes the Euclidian distance measure for industry. The results show that the coefficient on *Industry Diversification* remains positive and significant and that the coefficient on *Euclidian Industry* is negative and highly significant. These results give an even clearer picture of the effects of industry diversification on fund performance. The positive coefficient on *Industry Diversification* indicates that diversifying over industries positively affects fund performance, as documented previously. However, the negative coefficient on *Euclidian Industry* also shows that diversifying a great deal into industries in which managers have little or no past experience has a negative impact on fund performance. Because the second effect can also outweigh the first effect, the overall effect of industry diversification on fund performance depends on the industries into which managers choose to diversify. When managers diversify a great deal into industries in which they lack experience, high industry diversification can even have a negative overall effect on fund performance. Similarly, Model 2 includes both the *Stage Diversification* measure and the Euclidian measure for investment stage. The results show that the coefficient on *Euclidian Stage* is not significant while the coefficient on *Stage Diversification* is positive and highly significant at the 1% level. Therefore, diversifying into investment stages in which managers have little or no past experience does not significantly affect fund performance. Again, the reason may be due to follow-up investments in the same start-ups over several rounds. Overall, these results imply that past industry experience is more important for fund performance than past investment stage experience.

[Table 7 about here]

Models 3 to 6 explore whether investing heavily in different industries (stages) from the past affects the upside and downside risk of a fund. Models 3–8 assess the effects of the Euclidian distance measures on upside risk of the funds. The regression results imply that deviations from past industry and investment stage experience do not significantly affect managers' ability to pick the "stars" (i.e., portfolio companies with extraordinarily large returns and, thus, high upside volatility), as indicated by the non-significant coefficients on *Euclidian Industry* and *Euclidian Stage*. Similarly, Models 5–6 examine the effects of the Euclidian distance measure on downside risk of the funds. The results in Model 5 show that the coefficient on *Euclidian Industry* is positive and significant at the 5% level. This result is consistent with the regression results from Models 1 and 2 and suggests that a lack of proper industry experience increases the downside risk of a fund ("bad" risk); that is, it increases the likelihood of picking "losers." In contrast, Model 6 shows that deviations from past investment stage experience do not significantly affect downside risk, which again is consistent with the evidence in Models 1 and 2.

6. Discussion and concluding remarks

This study develops and tests a finance-related explanation for the positive effect of diversification (or lack of specialization) on the performance of VC funds. Because fund diversification also affects fund risk, risk-averse fund managers are tempted to invest in companies with higher idiosyncratic (i.e., company-specific) risk when pursuing a strong diversification strategy. In practice, diversification strategies are part of the private placement memorandum that VC fund managers use to secure capital commitments of limited partners. Doing so eventually leads to higher realized fund performance on average, since investments in riskier ventures only make sense if they come with better prospects of high returns. We tested this prediction using detailed information on a large sample of international VC funds. In contrast with most other studies, we measured performance by IRRs instead of indirect measures, such as initial public offering ratios. Similarly, our data allowed us to obtain good measures of fund risk. Our different results provide support for this risk channel, which highlights strategic considerations of VC fund managers in their investment decisions.

These findings provide several practical implications for entrepreneurs and VC fund managers. First is the importance of good fit with the expertise of the fund manager, as deviations from accumulated expertise lead to lower performance. While this implication is intuitive at first glance, it is not immediately obvious in light of the documented premium for diversified funds. A more consistent view is that diversified VC funds are run by more knowledgeable managers, who are less likely to deviate because, with their accumulated expertise, they are better able to match investments in different areas. Expertise is a key ingredient to the risk channel documented in this study. This directly affects the allocation of capital to riskier companies and, thus, entrepreneurs themselves. Entrepreneurs with riskier, possibly early-stage projects are more likely to receive funds from more diversified VC funds. Entrepreneurs are less likely to receive capital at the early stage from highly specialized funds, unless they are run by experienced VC managers. Less experienced managers are less likely to provide capital to early-stage ventures because of their lack of experience, unless they diversify to reduce their overall exposure to risk.

A second implication for entrepreneurs is that VC managers take a portfolio perspective when making investments, consistent with finance theory presumptions that individual investments should be viewed in terms of contribution to the portfolio rather than in isolation. Consistent with Dimov and De Clercq (2006), the investment strategy adopted by VC managers matters and affects the outcome of entrepreneurial firms. More specifically, the Risk Hypothesis proposed herein argues that performance and diversification should also be considered in light of risk implications, especially for industry diversification in which downside risk may increase as a result of more diversification. This means that entrepreneurs cannot expect VC managers to consider their start-ups an investment in isolation. This situation may become an issue particularly for entrepreneur with very risky projects. Even if their expected performance can compensate for the idiosyncratic higher risk, the willingness of VC managers to invest will also depend on what else they invested in, as some of the risk is reduced with diversification. Finally, our findings lend support to the view that expertise is accumulated only over a longer time horizon, given the persistence of diversification over time and the significant costs borne by deviations from previous investment areas.

Our study also offers implications for entrepreneurship literature. Whereas other studies have proposed alternative reasons VC managers may take a portfolio perspective and thus not necessarily choose the most promising projects (notably the hypothesis that VC managers have limited attention to devote to each entrepreneurial firm and therefore seek investments that fit ongoing investments; see Bernile et al., 2007; Cumming, 2006; Gifford, 1997; Jaaskelainen et al., 2006), this study proposes a new channel through which portfolio considerations may affect the choice of ventures and, thus, entrepreneurs seeking funding. Our results indicate that especially entrepreneurial ventures in the riskiest industries or at the early stage of development may be the most affected and would gain from a greater diversification of VC funds. We further find that experience can overcome the need for greater diversification, as more experienced VC firms can generate higher returns with lower diversification. The latter allows them to acquire more specialized knowledge in a given industry or stage of development, which will also benefit entrepreneurs.

References

Aguinis, H., Edwards, J.R., Bradley, K.J., 2016. Improving our understanding of moderation and mediation in strategic management research. Organizational Research Methods, forthcoming.

Ang, A., Chen, J., Xing, Y., 2006. Downside risk. Review of Financial Studies 19, 1191-1239.

Bali, T.G., Demirtas, K.O., Levy, H., 2009. Is there an intertemporal relation between downside risk and expected returns? Journal of Financial and Quantitative Analysis 44, 883–909.

Berger, A.N., Udell, G.F., 1998. The economics of small business finance: the roles of private equity and debt markets in the financial growth cycle. Journal of Banking and Finance 22, 613-73.

Bernile, G., Cumming, D., Lyandres, E., 2007. The size of venture capital and private equity fund portfolios. Journal of Corporate Finance 13, 564-590.

Campa, J., Kedia, S., 2002. Explaining the diversification discount. Journal of Finance 57, 1731–1762.

Cassar, G., 2004. The financing of business start-ups. Journal of Business Venturing 19 (2), 261-283.

Cochrane, J.H., 2005. The risk and return of venture capital. Journal of Financial Economics 75, 3-52.

Cressy, R., 2002. Funding gaps: a symposium. Economic Journal 112, F1-F16.

Cressy, R., Malipiero, A., Munari, F., 2014. Does VC fund diversification pay off? An empirical investigation of the effects of VC portfolio diversification on fund performance. International Entrepreneurship and Management Journal 10, 139-163.

Cressy, R., Munari, F., Malipiero, A., 2007. Playing to their strengths? Evidence that specialization in the private equity industry confers competitive advantage. Journal of Corporate Finance 13 (4), 647-669.

Cumming, D.J., 2006. The determinants of venture capital portfolio size: empirical evidence. Journal of Business 79 (3), 1083-1126.

Cumming, D., Dai, N., 2011. Fund size, limited attention and valuation of venture capital backed firms. Journal of Empirical Finance 18 (1), 2-15.

Cumming, D., Schmidt, D., Walz, U., 2010. Legality and venture capital governance around of the world. Journal of Business Venturing 25, 54-72.

Cumming, D., Walz, W., 2010. Private equity returns and disclosure around the world. Journal of International Business Studies 41, 727-754.

Dimov, D., De Clercq, D., 2006. Venture capital investment strategy and portfolio failure rate: a longitudinal study. Entrepreneurship Theory and Practice 30 (2), 207-223.

Ewens, M., Jones, C. M., Rhodes-Kropf, M., 2013. The price of diversifiable risk in venture capital and private equity. Review of Financial Studies 26 (8), 1854-1889.

Franzoni, F., Nowak, E., Phalippou, L., 2012. Private equity performance and liquidity risk. Journal of Finance 67, 2341-2373.

Gifford, S., 1997. Limited attention and the role of the venture capitalist. Journal of Business Venturing 12 (6), 459-482.

Gompers, P., 1995. Optimal investment, monitoring and the staging of venture capital. Journal of Finance 50 (5), 1461-1489.

Gompers, P., Lerner, J., 1998. Venture capital distributions: short-run and long-run reactions. Journal of Finance 53 (6), 2161-2183.

Gompers, P., Kovner, A., Lerner, J., 2009. Specialization and success: evidence from venture capital. Journal of Economics & Management Strategy 18 (3), 817-844.

Han, X., 2009. The specialization choices and performance of venture capital funds. Working paper. Available at: http://ssrn.com/abstract=1331057.

Harris, R.S., Jenkinson, T., Kaplan, S.N., 2014. Private equity performance: what do we know? Journal of Finance 69 (5), 1851-1882.

Hellmann, T., Puri, M., 2002. Venture capital and the professionalization of start-up firms: empirical evidence. Journal of Finance, 57 (1), 169-197.

Humphery-Jenner, M., 2012. Private equity fund size, investment size, and value creation. Review of Finance 16, 799-835.

Humphery-Jenner, M., 2013. Diversification in private equity funds: on knowledge sharing, risk aversion, and limited attention. Journal of Financial and Quantitative Analysis 48 (5), 1545-1572.

Jaaskelainen, M., Maula, M., Seppa, T., 2006. Allocation of attention to portfolio companies and the performance of venture capital firms. Entrepreneurship Theory and Practice 30 (2), 185-206.

Jackson III, W.E., Bates, T., Bradford, W.D., 2012. Does venture capitalist activism improve investment performance? Journal of Business Venturing 27, 342-354.

Kang, H.-G., Burton, R.M., Mitchell, W., 2011. How potential knowledge spillovers between venture capitalists' entrepreneurial projects affect the specialization and diversification of VC funds when VC effort has value. Strategic Entrepreneurship Journal 5 (3), 227-246.

Kanniainen, V., Keuschnigg, Ch., 2003. The optimal portfolio of start-up firms in venture capital finance. Journal of Corporate Finance 9, 521-534.

Knill, A., 2009. Should venture capitalists put all their eggs in one basket? Diversification versus pure-play strategies in venture capital. Financial Management 38, 441-486.

Korteweg, A., Sorensen, M., 2010. Risk and return characteristics of venture capital-backed entrepreneurial companies. Review of Financial Studies 23, 3738-3772.

Krohmer, P., Lauterbach, R., Calanog, V., 2009. The bright and dark side of staging: investment performance and the varying motivations of private equity firms. Journal of Banking and Finance 33, 1597-1609.

Lee, P., Wahal, S., 2004. Grandstanding certification and the underpricing of venture capital backed IPOs. Journal of Financial Economics 73, 375-407.

Lossen, U., 2009. The performance of private equity funds: does diversification matter? Working paper. Available on SSRN: http://ssrn.com/abstract=916702.

Markowitz, H., 1991. Portfolio Selection: Efficient Diversification of Investments, second ed. Basil Blackwell, Cambridge, MA.

Matusik, S.F., Fitza, M.A., 2012. Diversification in the venture capital industry: leveraging knowledge under uncertainty. Strategic Management Journal 33, 407-426.

Norton, E., Tenenbaum, B.H., 1993. Specialization versus diversification as a venture capital investment strategy. Journal of Business Venturing 8 (5), 431-442.

Phalippou, L., 2010. Venture capital funds: flow-performance relationship and performance persistence. Journal of Banking & Finance 34(3), 568-577.

Robinson, D.T., Sensoy, B.A., 2013. Do private equity fund managers earn their fees? Compensation, ownership, and cash flow performance. Review of Financial Studies 26, 2760-2797.

Robinson, D.T., Sensoy, B.A., 2016. Cyclicality, performance measurement, and cash flow liquidity in private equity. Journal of Financial Economics, forthcoming.

Ruhnka, J.C., Young, J.E., 1991. Some hypotheses about risk in venture capital investing. Journal of Business Venturing 6 (2), 115-133.

Seppa, T.J., Laamanen, T., 2001. Valuation of venture capital investments: empirical evidence. R&D Management 31 (2), 215-230.

Tobin, J., 1958. Liquidity preference as behavior towards risk. Review of Economic Statistics 25, 65–86.

Yang, Y., Narayanan, V.K., De Carolis, D.M., 2014. The relationship between portfolio diversification and firm value: the evidence from corporate venture capital activity. Strategic Management Journal 35, 1993-2011.

Table 1: Summary statistics of final sample: Panel A shows fund-level descriptive statistics (mean, median, standard deviations, minimum, and maximum values) for all variables used in the analysis. Panel B shows the matrix of pair-wise correlations between the variables. The IRR is the fund IRR based on all the investments made. *Industry Diversification* is equal to 1 – Herfindahl index of the industries in which the fund invested. *Stage Diversification* is equal to 1 – Herfindahl index of the stages in which the fund invested. The following seven stage categories are considered (in parentheses): Early Stage (seed, start-up, early stage), Later Stage (expansion, later stage), Buyout, and Other. *Fund Risk* is downside or upside fund volatility of the IRR. *US Dummy* is a dummy variable taking the value of 1 if the fund origin is the United States and 0 otherwise. *Portfolio Companies* is the number of portfolio companies in the fund. *Number of Professionals* is the number of professionals in the fund. *Ln(Fund Size)* is the natural logarithm of the fund's size. *Firm Age* is measured as the difference between founding date of the VC management firm and the fund's inception date. *Past Portfolio Companies* is the number of portfolio companies in which the VC firm invested prior to raising the current fund. *Number of Rounds* is the average number of investment rounds in which the fund participated, calculated as the number of investments made divided by the number of companies. *Ln(Investment Size)* is the natural logarithm of the average size of the fund's investment. ***, **, and * indicate significance at 1, 5, and 10, respectively

Panel A: Descriptive statistics		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Mean		0.355	0.657	0.466	0.471	1.231	0.700	32.893	22.668	18.662	18.001	51.082	3.887	15.178
Median		0.196	0.730	0.550	0.484	0.673	1.000	27.000	14.000	18.683	16.000	21.000	3.800	15.325
STD		0.615	0.222	0.247	0.149	1.643	0.459	19.263	44.587	1.250	8.918	84.456	1.584	0.965
Min		-0.306	0.000	0.000	0.000	0.017	0.000	7.000	2.000	15.425	0.420	0.000	1.100	12.494
Max		4.767	0.900	0.820	0.780	13.729	1.000	122.000	514.000	23.719	40.920	582.000	14.760	17.592
Panel B : Correlation matrix		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
IRR	(1)	**1**												
Industry Diversification	(2)	-0.0562	**1**											
Stage Diversification	(3)	0.0614	0.0134	**1**										
Fund Risk (Downside)	(4)	0.0073	-0.1210**	0.0759	**1**									
Fund Risk (Upside)	(5)	0.4707***	0.0775	-0.0597	0.1260**	**1**								
US Dummy	(6)	0.0081	-0.0608	-0.1199**	0.0453	0.0430	**1**							
Portfolio Companies	(7)	-0.0791	-0.2731***	-0.2079***	0.0723	-0.0442	0.0706	**1**						
Number of Professionals	(8)	0.0108	-0.1100**	-0.0103	-0.0482	-0.0387	0.0794	0.1029*	**1**					
Ln(Fund Size)	(9)	-0.2095***	-0.1645**	-0.2886***	-0.0386	-0.1031*	0.1627**	0.4072***	0.1481**	**1**				
Firm Age	(10)	0.0065	-0.1919**	-0.2446***	0.0031	-0.0188	0.1715**	0.4134***	0.2045**	0.2657***	**1**			
Past Portfolio Companies	(11)	-0.0809	-0.1683**	-0.1839**	-0.0421	-0.0911	0.1523**	0.4620***	0.1468**	0.3915**	0.3324***	**1**		
Number of Rounds	(12)	-0.2026***	0.0238	-0.0610	0.1559**	-0.1046*	0.0145	-0.0404	-0.1839**	0.1827**	0.0506	-0.0479	**1**	
Ln(Investment Size)	(13)	-0.2032***	-0.0541	-0.2452***	-0.0270	-0.0593	0.2343***	0.1850**	0.1550**	0.3048***	0.1866**	0.3080***	0.3039***	**1**

Table 2
Baseline analysis of the impact of diversification on performance.

This table shows OLS regression results. The dependent variable is the fund's IRR in Models 1 and 2, the fund's upside volatility in Models 3 and 4, and the fund's downside volatility in Models 5 and 6. All the explanatory variables are defined in Table 1. All the models include fund (vintage) year dummies. The values in parentheses are t-test values, based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Variables	IRR	IRR	Upside Vol	Upside Vol	Downside Vol	Downside Vol
Industry Diversification	0.1701*		0.2390*		0.1480***	
	(1.81)		(1.65)		(4.22)	
Stage Diversification		0.1321**		-0.0083		-0.0590*
		(2.53)		(-0.06)		(-1.72)
US Dummy	0.0509	0.0172	0.0056***	0.0052**	0.0011**	0.0021***
	(1.06)	(0.57)	(2.61)	(2.20)	(2.27)	(3.66)
Portfolio Companies	-0.0016	-0.0023**	0.1321*	0.1662**	0.0347*	0.0400**
	(-1.12)	(-2.59)	(-1.78)	(2.01)	(1.94)	(2.00)
Number of Professionals	0.0003	0.0004	-0.0004	-0.0005	0.0002	0.0002
	(0.74)	(1.58)	(-0.57)	(-0.66)	(0.96)	(0.97)
Ln(Fund Size)	0.0037	0.0214	-0.0033	0.0088	-0.0348***	-0.0358**
	(0.11)	(0.99)	(-0.06)	(0.15)	(-2.73)	(-2.53)
Number of Rounds	-0.0297**	-0.0198**	-0.0739***	-0.0783***	0.0169***	0.0201***
	(-2.20)	(-2.33)	(-3.82)	(-3.39)	(3.38)	(3.60)
Ln(Investment Size)	0.0341	0.0084	-0.0020	0.0278	-0.0242	-0.0169
	(0.86)	(0.33)	(-0.03)	(0.41)	(-1.63)	(-1.02)
Vintage Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No Obs.	308	308	308	308	308	308
Adj. R-square	0.360	0.364	0.38	0.345	0.285	0.293

Table 3: The impact of diversification on performance: the moderating role of VC firm experience.

This table shows OLS regression results for experienced VC firms using two measures of experience. The first measure (Panel A) is a dummy variable equal to 1 (0) if *Firm Age* is larger than (smaller than or equal to) the median of *Firm Age*. The second measure (Panel B) is a dummy variable equal to 1 (0) if *Past Portfolio Companies* is larger than (smaller than or equal to) the median of *Past Portfolio Companies*. Panel A shows the results for the first measure of VC firm experience, and Panel B shows the results for the second measure of VC firm experience. The dependent variable is the fund's IRR in Models 1 and 2, the fund's upside volatility in Models 3 and 4, and the fund's downside volatility in Models 5 and 6. All the other explanatory variables are defined in Table 1. All the models include fund (vintage) year dummies. The values in parentheses are t-test values, based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: First Measure of VC Experience						**Panel B: Second Measure of VC Experience**					
	Model 1A	**Model 2A**	**Model 3A**	**Model 4A**	**Model 5A**	**Model 6A**	**Model 1B**	**Model 2B**	**Model 3B**	**Model 4B**	**Model 5B**	**Model 6B**
Variables	**IRR**	**IRR**	**Upside vol**	**Upside vol**	**Downside vol**	**Downside vol**	**IRR**	**IRR**	**Upside vol**	**Upside vol**	**Downside vol**	**Downside vol**
Industry Diversification	0.0095		0.1710		0.1550***		0.0696		0.3300		0.1130**	
	(0.100)		(0.89)		(3.62)		(0.59)		(1.59)		(2.54)	
Industry Diversification × VC Experience	0.3840**		0.1740		-0.0131		0.2670		-0.2140		0.0858	
	(2.24)		(0.51)		(-0.17)		(1.45)		(-0.67)		(1.24)	
Stage Diversification		-0.0894		-0.2820**		-0.0541		-0.2250***		-0.2610***		-0.0721*
		(-1.53)		(-2.30)		(-1.28)		(-4.29)		(-3.38)		(-1.70)
Stage Diversification × VC Experience		0.318***		0.6430***		0.00537		0.4450***		0.3560***		0.0440
		(3.48)		(3.36)		(0.08)		(5.59)		(3.03)		(0.68)
US Dummy	0.0207	-0.0164	0.1510*	0.0369	0.0359*	0.0384**	0.0471	-0.0718***	0.1770**	-0.1040***	0.0337*	0.0348*
	(0.49)	(-0.63)	(1.80)	(0.68)	(1.94)	(2.05)	(0.97)	(-3.06)	(2.10)	(-3.01)	(1.86)	(1.84)
Portfolio Companies	-0.0017	-0.0029***	0.0055**	0.0052***	0.0013**	0.0017***	-0.0015	-0.0028***	0.0057**	0.0027***	0.0011**	0.0016***
	(-1.38)	(-3.72)	(2.20)	(3.11)	(2.27)	(2.99)	(-1.03)	(-3.94)	(2.22)	(2.65)	(2.05)	(2.89)
VC Experience	-0.2360**	-0.1190**	-0.1630	-0.2770***	-0.0001	0.0019	-0.1920	-0.1130**	0.0632	-0.0796	-0.0547	-0.00409
	(-2.01)	(-2.39)	(-0.69)	(-2.66)	(-0.00)	(0.05)	(-1.48)	(-2.58)	(0.28)	(-1.23)	(-1.13)	(-0.12)
Number of Professionals	0.0002	0.0002	-0.0005	0.0002	0.0002	0.0002	0.0003	-0.0001	-0.0007	-0.0003	0.0002	0.0002
	(0.600)	(0.94)	(-0.67)	(0.37)	(1.06)	(1.16)	(0.69)	(-0.31)	(-0.88)	(-0.80)	(1.00)	(1.23)
Ln(Fund Size)	0.0104	-0.0325*	-0.0097	-0.011	-0.0353***	-0.0313**	0.0056	-0.0267	-0.0131	-0.0155	-0.0336***	-0.0315**
	(0.35)	(-1.76)	(-0.17)	(-0.28)	(-2.74)	(-2.35)	(0.16)	(-1.62)	(-0.22)	(-0.64)	(-2.61)	(-2.36)
Number of Rounds	-0.0328***	-0.0569***	-0.0776***	-0.0524***	0.0176***	0.0159***	-0.0305**	-0.0615***	-0.0774***	-0.0557***	0.0169***	0.0162***
	(-2.84)	(-7.78)	(-3.36)	(-3.42)	(3.47)	(3.02)	(-2.27)	(-9.45)	(-3.29)	(-5.81)	(3.35)	(3.09)
Ln(Investment Size)	-0.0004	0.0571***	0.0318	-0.0087	-0.0232	-0.0276*	0.0332	0.0431**	0.0511	0.0959***	-0.0248	-0.0289*
	(-0.01)	(2.65)	(0.47)	(-0.19)	(-1.55)	(-1.78)	(0.83)	(2.23)	(0.73)	(3.37)	(-1.65)	(-1.85)
Vintage Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No Obs.	308	308	308	308	308	308	308	308	308	308	308	308
Adj. R-square	0.386	0.734	0.348	0.641	0.286	0.255	0.358	0.773	0.331	0.844	0.283	0.251

Table 4

Analysis of the impact of diversification and ex ante risk on performance.

This table shows OLS regression results. The dependent variable is the fund's IRR. *Downside Vol Ex Ante* is the downside volatility of all portfolio companies managed by the same VC firm before raising the current fund, and *Upside Vol Ex Ante* is the upside volatility of all portfolio companies managed by the same VC firm before raising the current fund. All other explanatory variables are defined in Table 1. All the models include fund (vintage) year dummies. The values in parentheses are t-test values, based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Variables	IRR	IRR	IRR	IRR	IRR	IRR
Industry Diversification	0.1701*		0.1515		0.1656	
	(1.81)		(0.89)		(0.97)	
Stage Diversification		0.1321**		0.1858		0.1724
		(2.53)		(1.33)		(1.22)
Downside Vol Ex Ante			0.5823**	0.5881**	0.5005*	0.5171*
			(2.20)	(2.24)	(1.85)	(1.85)
Upside Vol Ex Ante			0.0052	0.0030	0.0042	0.0023
			(0.25)	(0.14)	(0.20)	(0.11)
US Dummy	0.0509	0.0172			0.1541*	0.1435
	(1.06)	(0.57)			(1.75)	(1.63)
Portfolio Companies	-0.0016	-0.0023**	-0.0009	-0.0008	-0.0008	-0.0007
	(-1.12)	(-2.59)	(-0.38)	(-0.35)	(-0.34)	(-0.29)
Number of Professionals	0.0003	0.0004	-0.0001	0.0002	0.0001	0.0002
	(0.74)	(1.58)	(0.17)	(0.36)	(0.15)	(0.34)
Ln(Fund Size)	0.0037	0.0214	0.0325	0.0317	0.0281	0.0282
	(0.11)	(0.99)	(0.49)	(0.48)	(0.42)	(0.42)
Number of Rounds	-0.0297**	-0.0198**	-0.0376	-0.0352	-0.0380	-0.0358
	(-2.20)	(-2.33)	(1.52)	(-1.42)	(-1.53)	(-1.44)
Ln(Investment Size)	0.0341	0.0084	-0.0308	0.0254	0.0024	-0.0003
	(0.86)	(0.33)	(-0.42)	(0.35)	(0.03)	(-0.00)
Vintage Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No Obs.	308	308	179	179	179	179
Adj. R-square	0.360	0.364	0.356	0.364	0.362	0.367

Table 5

Industry diversification and fund risk.

The table reports instrumental variables (IV) GMM-based regression results. The dependent variable of Stage I equation (not reported) is the *Industry Diversification* for Models 1–3 and *Stage Diversification* for Models 4–6. The dependent variable in Models 1 and 4 (Stage II) is IRR, the dependent variable in Models 2 and 5 (Stage II) is the fund's upside volatility, and the dependent variable in Models 3 and 6 (Stage II) is the downside volatility. All the variables are defined in Table 1. The instrument in Stage I is the variable *Firm Age*. All the models in Stages I and II include fund (vintage) year dummies. Hansen j-test is the over-identification test, Relevance test assesses whether the instrumental variables are valid, and Exclusion test examines whether excluding variables from Stage I is relevant. The values in parentheses are t-test values, based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Stage II: Regression Analysis					
Variables	**Model 1** Dep. Var. = IRR	**Model 2** Dep. Var. = Upside Vol	**Model 3** Dep. Var. = Downside Vol	**Model 4** Dep. Var. = IRR	**Model 5** Dep. Var. = Upside Vol	**Model 6** Dep. Var. = Downside Vol
Industry Diversification	0.1247*	0.0052**	0.1617***			
	(1.81)	(2.21)	(5.00)			
Stage Diversification				0.1722**	0.0056**	-0.3871**
				(3.03)	(2.36)	(-2.48)
US Dummy	0.0482	0.3119**	0.0354**	0.0178	-0.6632	0.0629**
	(1.29)	(2.10)	(2.02)	(0.54)	(-0.94)	(2.90)
Portfolio Companies	-0.0015	0.1527*	0.0011**	-0.0061	0.2061**	0.0017***
	(-1.38)	(1.90)	(2.29)	(-0.78)	(2.10)	(3.18)
Number of Professionals	0.0031	-0.0007	0.0001	0.0004	-0.0007	0.0002
	(0.88)	(-0.94)	(0.74)	(1.35)	(-0.83)	(0.98)
Ln(Fund Size)	0.0145	-0.0107	-0.0327**	-0.0381*	-0.0101	-0.0376***
	(0.54)	(-0.19)	(-2.63)	(-1.91)	(-0.17)	(-2.86)
Number of Rounds	-0.0320***	-0.0842***	0.0152***	-0.0111	-0.0823***	0.0156***
	(-3.04)	(-3.73)	(3.09)	-(1.43)	(-3.56)	(3.05)
Ln(Investment Size)	0.0005	0.0399	-0.0221	0.1244***	0.0662	-0.0073
	(0.210)	(0.60)	(-1.53)	(4.84)	(0.87)	(-0.43)
Hansen j-test	3.641	4.408	1.871	2.279	2.882	3.798
Relevance test	7.268	6.463	11.530	2.453	2.299	2.763
Exclusion Criteria test	0.507	0.7255	0.763	0.382	0.157	0.150
Vintage Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No Obs.	308	308	308	308	308	308

Table 6

Persistence in diversification.

This table shows persistence in diversification using OLS regression analysis. The dependent variable in Models 1 and 2 is the industry diversification of the current fund, and the dependent variable in Models 3 and 4 is the investment stage diversification of the current fund. *Industry Diversification (Previous)* is the industry diversification of all previously managed VC funds of the same VC firm, and *Stage Diversification (Previous)* is the investment stage diversification of all previously managed VC funds of the same VC firm. All other variables are as defined in Table 1. The values in parentheses are t-values, based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	Industry Diversification	Industry Diversification	Stage Diversification	Stage Diversification
Industry Diversification (Previous)	0.8641***	0.8361***		
	(20.57)	(15.29)		
Stage Diversification (Previous)			0.6690***	0.6740***
			(8.74)	(8.54)
Firm Age		-0.0005		-0.0013
		(-0.60)		(-0.80)
Ln(Fund Size)		0.0030		0.0232
		(0.20)		(1.57)
Number of Professionals		0.0002		0.0007***
		(1.31)		(2.66)
Vintage Year Dummies	Yes	Yes	Yes	Yes
No Obs.	179	179	179	179
Adj. R-square	0.661	0.682	0.455	0.473

Table 7

Extended performance and risk regressions.

This table shows the effect of the Euclidian distance measures for industry (*Euclidian Industry*) and investment stage (*Euclidian Stage*) on the fund's upside and downside risk. The Euclidian measures are calculated for each fund using Equation (8). All other variables are as defined in Table 1. The values in parentheses are t-values, based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Variables	IRR	IRR	Upside Vol	Upside Vol	Downside Vol	Downside Vol
Industry Diversification	0.1921**		0.3070		0.1562***	
	(2.52)		(1.61)		(3.15)	
Stage Diversification		0.1661***		-0.0295		-0.0389
		(2.75)		(-0.15)		(-0.80)
Euclidian Industry	-0.3770***		-0.1472		0.1530**	
	(-3.82)		(-0.60)		(2.37)	
Euclidian Stage		0.0753		0.0855		0.0576
		(1.36)		(0.49)		(1.29)
US Dummy	-0.0751*	0.0339	0.1572	0.2701**	0.0509**	0.0588**
	(-1.97)	(0.96)	(1.65)	(2.42)	(2.03)	(2.06)
Portfolio Companies	-0.0030***	-0.0017*	0.0057**	0.0067**	0.0019***	0.0022***
	(-2.74)	(-1.76)	(2.07)	(2.18)	(2.67)	(2.72)
Number of Professionals	0.0005	0.0005	-0.0001	-0.0005	-0.0010*	-0.0014**
	(1.42)	(1.54)	(-0.16)	(-0.48)	(-1.96)	(-2.36)
Ln(Fund Size)	0.0401	0.0459*	-0.0062	0.0071	-0.0436**	-0.0345*
	(1.42)	(1.77)	(-0.09)	(0.09)	(-2.39)	(-1.66)
Number of Rounds	-0.0345***	-0.0039	-0.0670**	-0.0656**	0.0227***	0.0199**
	(-3.31)	(-0.41)	(-2.57)	(-2.15)	(3.28)	(2.51)
Ln(Investment Size)	0.0252	-0.0285	-0.0372	-0.0718	-0.0090	-0.0055
	(0.76)	(-0.94)	(-0.45)	(-0.75)	(-0.41)	(-0.22)
Vintage Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No Obs.	179	179	179	179	179	179
Adj. R-square	0.712	0.754	0.709	0.458	0.333	0.166