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Article

Diversification and Fund Performance—An Analysis of Buyout Funds

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Abstract: This paper studies the relationship between portfolio diversification and fund performance, based on an unexplored, hand-collected dataset of buyout funds. The dataset comprises detailed information at the level of portfolio companies, which allows measuring the concentration of the fund portfolios towards individual companies, industrial, and geographical focus. Our results suggest that diversification within, but not across industries, associates with higher buyout fund performance. We do not find a significant relationship between geographical diversification and performance. These results partly contradict results documented in prior literature.

Keywords: performance; buyout funds; diversification; systematic risk

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1. Introduction

This paper provides an empirical analysis of the relationship between portfolio diversification and fund performance of buyout funds. The exposure of buyout funds to projects that are typically characterized by substantial idiosyncratic risk makes them an interesting case to study the link between diversification and performance. Despite the relevance of the topic for both investors and academics alike, the existing literature is scarce, published papers primarily focus on venture capital funds, and reported empirical results remain inconclusive. Our paper contributes to this literature by focusing on buyout funds. We analyze a proprietary, unexplored dataset that allows measuring diversification by the Herfindahl–Hirschman Concentration Index (HHI), which is a more precise metric than the number of portfolio companies that has been used as a proxy for fund diversification in prior studies on private equity, including buyout fund performance (e.g., Humphery-Jenner 2012, 2013).[1] Further, our study controls for systematic risk.

A distinctive feature of private equity funds is that they actively engage in their investments. In addition to the capital they invest, private equity managers closely monitor and support their portfolio companies (e.g., Hellmann and Puri 2002; Metrick and Yasuda 2011). They contribute their experience and network, usually sit on the board of directors, and are actively involved in strategic decisions. Such monitoring and mentoring activities, however, are both costly and time consuming. Therefore, private equity managers can oversee a limited number of investments only

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1 The HHI has been used in related studies on venture capital performance. For the larger class of private equity funds, which include both venture capital and buyout funds, two exceptions are the working papers by Ljunqvist and Richardson (2003) and Lossen (2006).

(e.g., Gompers and Lerner 2000; Diller and Kaserer 2009), which leaves the fund exposed to considerable idiosyncratic risk. As idiosyncratic risk is not compensated with a risk premium (i.e., is not priced) according to modern portfolio theory, the standard advice to investors is to hold diversified portfolios, which generally yield higher risk-adjusted returns.

However, this conventional wisdom may not be directly applicable to private equity funds. Ewens et al. (2013), for example, developed a model that implies that idiosyncratic risk must be priced in private equity transactions and, therefore, can be positively related to the fund's return. Their empirical evidence supports the model. Further, a fund's decision not to diversify, but to focus its investment activities on particular companies, industries or spatial regions may affect returns in a more direct way: as a substantial part of the private equity business model builds on the close interaction of the fund's managers and its portfolio companies, Das et al. (2003) argue that the investment success of a private equity fund is likely to be positively related to the managers' skills, and expertise in monitoring and developing their portfolio companies. Given that these skills are a costly resource, it appears appropriate to assume that specialized funds have a higher level of skills, and informational advantages in their area, or industry, of expertise (e.g., Cressy et al. 2014) translate into superior performance.[2]

The empirical evidence is mixed. Results reported by Cumming and Dai (2010), Knill (2009), and Gompers et al. (2009) suggest that specialization (i.e., less diversification) implies superior performance for venture capital funds. Cressy et al. (2014) report that venture capital funds' success is positively related to geographical diversification, while the relationship is negative for industry diversification. Turning to studies that include buyout funds, results reported by Humphery-Jenner (2012, 2013) suggest a positive relationship between industrial or geographical diversification, and private equity returns. His sample includes both venture capital and buyout funds, however, the performance results are not disaggregated by investment style. Ljunqvist and Richardson (2003) report that private equity returns tend to be negatively related to portfolio diversification, although results in most specifications are statistically insignificant, in particular for buyout funds. Lossen (2006) reports a positive relationship between fund performance and industry diversification, but acknowledges that his sample is severely biased, as it only includes funds with positive returns, which impedes to generalize these results for the private equity industry as a whole. Table A1 in Appendix A summarizes the key results and approaches in the existing literature.

Diversification is typically measured as a fund's number of investments in a particular industry or spatial region. As pointed out by Lossen (2006), a simple count metric may not comprehensively reflect the diversification characteristics of a particular fund, given that individual investments of a fund are heterogeneous in size. Further, funds may have a few, potentially small co-investments in industries or areas outside their traditional focus, which may overstate diversification in a count metric. In this paper, we therefore use the HHI as a more precise measure of portfolio diversification in general, and in terms of industrial or geographical concentration of a fund's investments. This, in comparison to prior studies, is possible given the nature of our data, which consists of a unique, hand-collected sample of buyout funds, for which we observe time-series of year-end valuations of each of the 140 fund's investments as well as the full history of cash flows. The application of the HHI and the control for systematic risk have important implications on the empirical results: our results based on the naive diversification measure are in line (yet not statistically significant) with the results reported by Humphery-Jenner (2012, 2013). Consistent with his findings, our results suggest that diversification across companies, industries or geographical areas is positively related to a fund's internal rate of return (IRR). In contrast, our results based on the HHI suggest that industry specialization is associated with higher IRR's for buyout funds. These findings are qualitatively unchanged when we control for

[2] The benefit of informational advantages and skills in actively managed, concentrated portfolio has also been documented for mutual funds (e.g., Kacperczyk et al. 2005).

systematic risk, but do not remain statistically significant. We do not find any significant relationship between buyout fund performance and geographic diversification.

The remainder of this paper is structured as follows. In Section 2, we describe the data, variables and methods used in this study. In Section 3, we present the empirical results. In Section 4 we summarize the results in the context of the existing literature and conclude.

2. Data, Variables, and Methods

The analysis in this paper is based on a proprietary dataset that has been hand-collected from a cross section of Swiss pension funds (SPF), which granted exclusive access to their investment schemes for the purpose of this study.[3] Specifically, the pension funds provided data for their complete history of fund investments since the inception of their individual private equity portfolios. Importantly, the SPF's in our sample do not raise, or manage own buyout funds, but rather commit capital to third-party funds, where the funds' managers (the general partners, GPs) are generally independent from the SPF.

The combined dataset comprises information on 167 buyout funds that were raised between 1993 and 2012. The information was made available to us on the portfolio level of the underlying private equity funds. Specifically, in addition to fund level characteristics such as fund size, vintage year or target market, pension funds provided the entire cash flow history (net of fees) at the fund level. For funds that are not liquidated by the end of our observation period, we observe the GP's estimates of unrealized net asset value (NAV). Further, we have access to yearly (re-) valuations of all individual portfolio companies of each fund. The latter information is the major advantage of our dataset, as it allows measuring diversification from the HHI index.

Another advantage of our dataset is that it is directly sourced from investors (the limited partners, LPs), rather than collected from GPs, which may reduce the likelihood of self-selection, or survivorship biases arising from a selective disclosure of information for successful investments only. While we cannot be absolutely certain that the information provided to us is entirely complete, we have taken reasonable precautions to minimize the risk of strategic disclosures. We declared, for example, in a non-disclosure agreement signed with each individual SPF to publish the information made available to us only in aggregated form (across SPFs), such that individual SPFs are not identifiable.

An important drawback of our dataset stems from the homogeneous group of LP's, all of which are pension funds, and all of which are based in Switzerland. SPFs in our sample may therefore have similar preferences in selecting funds (or fund managers), which in turn could bias our results, and inference. In the context of our study, the bias can be severe, if SPFs systematically have a preference for either specialist, or generalist funds. While discussions with the SPFs' investment officers suggest that this is not the case, we cannot verify their claim from the data provided to us. We learned, however, from these discussions that SPFs rarely invest in "Mega-Buyouts". This preference is also clearly visible in our sample, as is discussed in Section 2.1.

Further, while we observe some heterogeneity in the average performance across SPFs, we do not find evidence that SPFs systematically have superior (or worse) fund picking abilities, as we discuss in Section 2.1. Another concern is a potential home bias in the investments of the selected funds. However, with Swiss portfolio companies accounting for 0.45 percent of the portfolio companies in our sample, this concern appears unlikely. Finally, our dataset does not include the names of the funds, or a comprehensive set of fund characteristics, which limits our ability to control for potentially relevant variables (e.g., the experience of the GPs' management teams) in our empirical analysis.

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3 SPFs in our sample shared their data on a voluntary basis. Generally, pension funds in Switzerland are private institutions, which do not fall under a similar mechanism to what is known in the United States as the "Freedom of Information Act". While a similar act exists in Switzerland (termed "Bundesgesetz über das Öffentlichkeitsprinzip der Verwaltung"), it is confined to promoting transparency with regard to the mandate, organization and activities of the Administration.

2.1. Sample

For the empirical analysis we restrict our sample to buyout funds that are either liquidated or have started to draw down committed capital. This leaves funds with vintage years until, and including the year 2011 in our sample. We further exclude vintage years prior to 1998, which is the first year in our dataset that contains more than one fund. Applying these restrictions leaves a sample of 140 funds, 2510 portfolio companies, comprising 8661 fund level cash flows.

Table 1 summarizes the sample characteristics for the full sample of funds, as well as according to clusters of vintage years (Panel A), and the distribution of the fund portfolio companies by geography and industry in Panel B. Most of the funds were started in the second half of the sample period between 2006 and 2011.

In terms of committed capital, the table shows that the funds in which SPFs in our sample invest grew from an average of USD 114 million (mn) in 1998/1999 to USD 475 mn in 2006/2007, which forms a peak in fund size. Funds raised in later vintage years are characterized by slightly lower volumes. The funds in our dataset appear to be slightly smaller, compared to fund sizes reported in other studies. Robinson and Sensoy (2016), for example, report an average fund size of USD 737 mn. Harris et al. (2014) report that the average buyout fund size in the 1990s and 2000s has a committed capital of USD 782 mn and USD 1420 mn respectively.

Table 1. Size and performance characteristics of sampled funds.

Panel A: Fund Level Characteristics							
Vintage Years	No.	Size (mn)		IRR		PME	
	Funds	Median	Mean	Median	Mean	Median	Mean
1998–1999	11	72.0	113.5	0.09	0.09	1.46	1.42
2000–2001	16	192.6	221.9	0.19	0.19	1.52	1.52
2002–2003	3	270.0	242.6	0.39	0.31	1.60	1.56
2004–2005	18	238.0	314.6	0.09	0.14	1.36	1.49
2006–2007	38	311.8	474.6	0.07	0.08	1.19	1.22
2008–2009	24	163.5	280.0	0.08	0.09	0.98	1.01
2010–2011	30	180.4	247.2	−0.02	−0.06	0.91	0.97
Full Sample	140	193.7	309.7	0.07	0.07	1.09	1.22

Panel B: Portfolio Companies by Geography and Industry			
Geographical Region	No. Companies	GICS Sector	No. Companies
North America	1222	Consumer Discretionary	606
South America	22	Industrials	377
Western Europe	827	Health Care	303
Eastern Europe	111	Information Technology	320
Asia	269	Financials	282
Australia/Pacific	20	Energy	104
Africa	7	Materials	31
Global	3	Consumer Staples	21
Other	29	Teleco Services	41
		Utilities	6
		Co-Inv. Fund of Funds	13
		Other/Unknown	406
Full Sample	2510		2510

Notes: this table presents characteristics of the 140 buyout funds in the sample. Panel A shows fund level information such as size and performance measures. The median and mean fund size reflects the committed capital in USD million (mn). The variables IRR and PME refer to the internal rate of return and Public Market Equivalent. Panel B displays geographical and sectoral breakdown of the 2510 portfolio companies. GICS refers to Global Industry Classification Standard and Co-Inv. to Co-Investments.

2.2. Performance Measures (Dependent Variables)

We use the natural logarithm (log) of the internal rate of return (IRR) as our first dependent variable. The IRR is defined as the discount rate that makes the net present value of a stream of cash inflows and outflows equal to zero. We calculate the IRRs for each individual fund from the fund's complete cash flow history. For not yet liquidated funds, we follow the convention of Kaplan and Schoar (2005) and use the last available NAV (31 December 2012) as a proxy for the final distribution to the investor.

The distribution of IRRs, according to clusters of vintage year are reported in Table 1. The buyout funds in our sample generated a median and mean IRR of 7 percent. Funds with vintage years 2000 to 2005 generally outperform funds raised in other years. Buyout funds in the vintage year cluster 2002–2003 are exhibiting the highest IRR (31 percent), but are relatively underrepresented in our sample. This pattern, as well as median and mean IRRs are qualitatively similar to returns reported in recent studies. Robinson and Sensoy (2016) report a mean and median IRR of 9 percent. Higson and Stucke (2012) document a mean IRR of 11% and a median IRR of 9%. Harris et al. (2014) report a mean and median IRR of 14% and 13%.

Although useful, the IRR has several important drawbacks. First, it is highly sensitive to timing of the fund's cash flows. The timing of capital calls and distributions, however, is at the full discretion of the fund managers. Investors therefore are sometimes concerned that GPs may use that flexibility to manipulate IRRs to some extent, in particular at times when new funds are raised.[4] Recent results reported by Gredil (2018) and Jenkinson et al. (2018), however, suggest that GPs have timing abilities, which are a potential source of returns for investors. The incremental value of timing abilities is reflected in the IRR making it a relevant measure for the assessment of fund performance. However, the IRR is an absolute, not a relative performance measure, which does not control for market movements or systematic risk. We therefore use the Public Market Equivalent (PME) as a second dependent variable. Following Kaplan and Schoar (2005), the PME is calculated as the sum of all discounted cash outflows over the sum of the discounted cash inflows, where the realized total return of a public market index is used as the discount rate. Following a common standard in the literature, we use the returns of the Standard and Poor (S&P) 500 as our default specification, but also report results based on the Morgan Stanley Capital International (MSCI) World index as an alternative specification. As shown by Sorensen and Jagannathan (2015) and Korteweg and Nagel (2016), the Kaplan and Schoar (2005) PME implicitly accounts for necessary adjustments resulting from differences in systematic risk between the private equities and public markets, if investors have log utility. However, if investors do not have log utility, the Kaplan and Schoar (2005) PME distorts inference about the abnormal performance of the private funds, as shown by (Korteweg and Nagel 2016), by placing a restriction on the equity premium. The authors show that abnormal performance is overestimated in rising public equity markets, if the portfolio companies beta exceeds one (and vice versa). Following earlier approaches in the literature (e.g., Robinson and Sensoy 2016), we therefore also calculate a levered PME, by adjusting public market returns with a fund-specific beta, which is calculated from the actual portfolio composition of the individual funds in our sample. Specifically, in each year of the fund's life, we calculate a value weighted beta, where the fund's aggregate allocation towards the portfolio companies' industries serves as the weight. The funds in our sample have a median PME of 1.09 and a mean PME of 1.22, implying an outperformance of 9% to 22% over the life of the funds relative to the S&P 500 Index. Splitting the sample into clusters of vintage years indicates a similar pattern as is observed for the IRR: earlier funds tend to perform better than more recent funds, again with the vintage years 2002–2003 showing the highest performance (mean PME 1.56). The observed PMEs are well in line with PMEs reported by Higson and Stucke (2012), Harris et al. (2014), Phalippou (2014), and Robinson and Sensoy

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[4] GP's reporting behavior, and the issue of potential biases and manipulation in the context of information asymmetry is extensively discussed by, e.g., Johan and Zhang (2020).

(2016) who report mean PME between 1.19 and 1.22 and median PME between 1.09 and 1.16 in their samples, relative to the S&P 500 Index. Table A2 in Appendix A provides a comparison of performance documented in recent studies.[5]

2.3. Diversification Measures (Independent Variables)

We study the diversification effects in a private equity fund across three different dimensions: (i) portfolio companies, (ii) industries, and (iii) geographical regions. Following earlier studies (e.g., Humphery-Jenner 2012, 2013), in a first step, we measure diversification by the absolute number of individual portfolio companies, industries or geographies in a fund's portfolio. We refer to this count metric as the "naive" diversification measure. However, although informative, a simple count metric may not comprehensively reflect the diversification characteristics of a particular fund, given that individual investments of a fund are heterogeneous in size (e.g., Lossen 2006). Further, funds may have a few, potentially small co-investments in industries or areas outside their traditional focus. In this paper, we therefore use the Herfindahl–Hirschman Concentration Index (HHI) to proxy for the portfolio diversification of a fund, including industrial and geographical diversification.

We calculate the HHI as the sum of the squared weights of the (undiscounted initial) investments of a private equity fund in each dimension, relative to the sum of all (undiscounted initial) investments as a more precise measure of portfolio diversification.[6] We use initial investments (i.e., the first valuation of the portfolio company), as we only observe valuations at each year-end, and cannot discriminate between valuation changes due to follow-on investments and changes resulting from revaluations. We acknowledge that this procedure may not be fully adequate for staged investments (i.e., multiple investment rounds). Given that our paper focuses on buyout funds, and substantial staged investments are more common in venture capital funds, a potential bias is expected to be small. The HHI is bounded between values from zero to one, whereas a HHI of zero indicates a perfectly diversified fund, and a HHI of one indicates that the fund is not diversified at all. In our regression analysis, we therefore transform the HHI variable to "1-HHI" for easier interpretation, as regression coefficients calculated from the transformed variable have the same sign as those calculated from the count metric, where higher values indicate more diversified portfolios. Nevertheless, all figures we present for the HHI in Table 3 follow the usual convention and report the non-transformed measure.

Furthermore, in contrast to earlier studies (e.g., Humphery-Jenner 2013), we assign the individual portfolio companies to geographical categories of similar size (i.e., regions). Specifically, we calculate diversification measures from larger geographical areas, such as "Western Europe", rather than counting individual countries (e.g., Austria, France, Germany, Switzerland, or Liechtenstein) as separate occurrences. To assign individual industries and industry branches to larger sectors in a similar procedure, we use the Global Industry Classification Standard (GICS), developed by Morgan Stanley Capital International (MSCI) and Standard and Poor (S&P). The classification consists of 11 industries (termed sectors in the GICS scheme). The correlations between naive and HHI-based diversification measures, and the natural logarithm of the fund size, which serves as an additional control, are reported in Table 2. The table shows that both measures are substantially, but not perfectly correlated. The highest correlation coefficient (0.85) is observed between the two industry, and the two geographical diversification measures.

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[5] For a discussion of historical private equity performance see, e.g., Kaplan and Sensoy (2015).

[6] The index is calculated as follows: $\sum_{i=1}^{N} p_i^2$, where "p" is the weight of the i-th group in a specific category (e.g., industries). In the case of all investments having the same value, the HHI takes the value of 1/N.

Table 2. Correlations of independent variables.

No.	Independent Variables	1	2	3	4	5	6	7
1	logComp	1						
2	logIndu	0.75 ***	1					
3	logGeo	0.62 ***	0.47 ***	1				
4	hhiComp	0.75 ***	0.66 ***	0.42 ***	1			
5	hhiIndu	0.60 ***	0.85 ***	0.35 ***	0.66 ***	1		
6	hhiGeo	0.40 ***	0.32 ***	0.85 ***	0.31 ***	0.22 ***	1	
7	logSize	0.47 ***	0.43 ***	0.59 ***	0.30 ***	0.37 ***	0.49 ***	1

Notes: This table reports Pearson's correlation coefficients of the independent values (mean values) for the sample of 140 buyout funds. LogComp, logIndu, logGeo are the naive diversification variables for the number of companies, number of industries, and number of geographies (reported in numerical values). The variables hhiComp, hhiIndu, hhiGeo are the Herfindahl–Hirschman indices (HHI) measuring the concentration of companies, industries, and geographies in a fund (reported in %). LogSize refers to the natural logarithm of fund size in USD million, measured as committed capital. Significance at the 1%, 5% and 10% levels are indicated by ***, **, and *.

Table 3 summarizes the distributional characteristics of diversification measures of the funds in our sample. Diversification across the different dimensions varies substantially. On average, funds in our sample invest into approximately 18 portfolio companies, across 5 different industry sectors in two geographical areas. Measured by the HHI, mean values are 0.15 for diversification on the portfolio company level, 0.38 for geographical diversification and 0.80 for industry diversification.

2.4. Empirical Estimation

For the empirical analysis, we use ordinary least squares (OLS) regressions. We refrain from including both naive diversification measures and HHIs in the same model in order to avoid potential issues arising from multicollinearity. All models include vintage year-fixed effects.

Table 3. Characteristics of diversification variables.

	No.	**Number of Port. Companies**		**Number of Industries**		**Number of Geographies**		**HHI Port. Companies**		**HHI Industries**		**HHI Geographies**	
Vintage Years	**Funds**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**
1998–1999	11	16.00	17.45	4.00	4.55	2.00	2.09	0.14	0.15	0.36	0.40	0.87	0.81
2000–2001	16	21.50	27.19	5.00	5.31	2.00	2.44	0.10	0.16	0.29	0.35	0.85	0.76
2002–2003	3	11.00	13.67	4.00	3.67	1.00	1.33	0.11	0.11	0.33	0.35	1.00	0.91
2004–2005	18	16.00	19.17	5.00	5.50	2.00	2.61	0.09	0.10	0.28	0.31	0.76	0.75
2006–2007	38	16.00	23.45	5.00	5.18	2.00	2.45	0.10	0.11	0.32	0.36	0.79	0.75
2008–2009	24	11.00	15.29	5.00	5.17	1.50	1.96	0.12	0.13	0.29	0.34	0.97	0.84
2010–2011	30	5.50	7.97	3.50	3.50	1.00	1.57	0.23	0.27	0.39	0.50	1.00	0.85
Full Sample	140	13.00	17.93	5.00	4.79	2.00	2.14	0.12	0.15	0.32	0.38	0.87	0.80
		IQR	Std	IQR	Std	IQR	Std	IQR	Std	IQR	Std	IQR	Std
		13.00	17.15	2.00	1.78	1.00	1.26	0.09	0.15	0.18	0.20	0.39	0.22

Notes: this table presents distributional characteristics of the diversification variables. Number of portfolio companies, industries and geographies are reported in numerical values. Herfindahl–Hirschman indices (HHIs) measures concentration of companies, industries and geographies in a fund and are reported in %. Standard deviation (Std) and interquartile range (IQR) are reported too.

3. Empirical Results

In this section, we turn to the relationship between diversification of buyout fund portfolios and their returns. Empirical results across different model specifications are presented in Table 4. We start our discussion with the logarithm of the internal rate of return (logIRR) as the dependent variable. Considering the naive diversification measure as the relevant proxy (Column I), we find a positive sign for all coefficients (logComp, logGeo, and logIndu—the natural logarithm of the number of companies, number of geographies, and number of industries). In principle, and consistent with the results reported by Humphery-Jenner (2012, 2013), these findings indicate that funds with a more diversified portfolio tend to generate a higher IRRs. However, none of the coefficients is statistically significant.[7] To quantify the economic significance of the diversification effect, we calculate the difference between the fitted IRRs for funds in different percentiles of the diversification distribution. With respect to the number of companies (logComp), the respective difference between the 10th, and 90th percentile fund is substantial, at 8.78 percent, and the spread in IRRs between the 25th, and 75th percentile fund is 4.33 percent (not reported). Differences for funds in the logGeo, and logIndu percentiles are considerably smaller, ranging between 0.24 percent, and 0.62 percent.

These results change, when we use the transformed HHI variables (Column II) as the relevant measure for diversification. While the coefficient for diversification in terms of the number of portfolio companies (hhiComp) remains positive, the coefficient for industry diversification becomes negative (hhiIndu, the concentration of industries in a fund). The coefficients are statistically significant at the 1 percent, and 10 percent level respectively. The differences in fitted IRRs are 8.71 percent (75th minus 25th percentile, hhiComp), and 2.5 percent (hhiIndu). We do not find any statistically significant relationship between geographical diversification and fund returns. These results suggest that while diversification in general (i.e., across a larger number of portfolio companies) is associated with higher returns, funds that diversify within their specific area of expertise are more successful. In this respect, a focus on industry expertise, rather than a geographical focus is decisive.

Table 4. Results from ordinary least squares (OLS) estimates.

Independent Variables	Dependent Variable					
	logIRR		PME		PME (Beta Adjusted)	
	I	II	III	IV	V	VI
logComp	0.042		0.053		0.040	
	(0.20)		(0.54)		(0.66)	
logGeo	0.003		0.070		0.073	
	(0.94)		(0.46)		(0.45)	
logIndu	0.006		−0.096		−0.104	
	(0.90)		(0.42)		(0.39)	
hhiComp		0.554 ***		0.513		0.502
		(0.00)		(0.13)		(0.15)
hhiGeo		0.030		0.100		0.050
		(0.65)		(0.59)		(0.80)
hhiIndu		−0.155 *		−0.326		−0.359
		(0.07)		(0.17)		(0.15)
logSize	−0.026	−0.029 **	−0.117 ***	−0.107 ***	−0.117 **	−0.105 ***
	(0.14)	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)
Adj. R^2	0.220	0.331	0.253	0.263	0.285	0.294

Notes: This table presents regression coefficient estimates of the relation between the natural logarithm of the internal rate of return (logIRR) as well as the Public Market Equivalent (PME) as the dependent variables and explanatory variables. The coefficients are estimated using ordinary least square (OLS) estimates. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *. *p*-values are reported in parentheses. Adj. R^2 refers to the coefficient of determination of the regression. All specifications include vintage year-fixed-effects. The sample consists of 140 buyout funds.

Our results remain qualitatively unchanged, when timing aspects and systematic risk are taken into account. This perspective is relevant, as funds, whose investments fall into favorable market

[7] The lack of significance may certainly well be a result of our smaller sample. However, *p*-values, in particular for geographical and industry diversification, are far from zero.

conditions, or funds that invest in industries which exhibit a higher systematic risk may be more likely to generate higher returns. We control for these differences along two dimensions: first, we use the PME, which reflects the fund's returns relative to public equity, as the dependent variable in our model. Second, we use a beta adjusted PME, which takes the sensitivity of the fund's main target industry into account. The results are reported in Columns III and IV of Table 4 for the PME. Columns V and VI report the results for the adjusted PME.

Regressing the diversification measures on the PME yields the same sign for all coefficients, in both specifications of the model (naive and HHI). However, the coefficients for portfolio company and industry diversification are no longer statistically significant, suggesting that the relationship between diversification and fund performance is rather weak. The effect, however, is economically significant, with differences in PMEs of 0.06, and 0.14 between funds at the 75th and 25th, and 90th and 10th percentiles, for the hhiIndu, and 0.05, and 0.11 for the hhiComp measure, respectively. The effect for the hhiGeo measure is 0.04, between the 25th and 75th percentile. These results also hold, if the beta adjusted PME is used as the dependent variable.

In all specifications, we find a negative relationship between fund size and performance, which is statistically significant in most regressions. This finding is in contrast to results reported in prior literature. Robinson and Sensoy (2016), for example, report fund size is positively associated, whereas Lopez-de-Silanes et al. (2015) or Harris et al. (2014) do not find a statistically significant relationship between fund size and buyout fund returns. Our finding may be a result of our sample composition, which includes a higher proportion of smaller buyout funds.[8]

To assess the robustness of our results, we consider several modifications to (i) the performance measure in our model, presented in Table A3 in the Appendix A, and (ii) modifications to our diversification variables, presented in Table A4 in the Appendix A.[9] First, we log transform the PME and the beta adjusted PME variables, to address our concern that the lack of power observed in our main specification might be driven by potential outliers. Our results, however, remain qualitatively and quantitatively unchanged (Columns I to IV). The results also remain unchanged, when we use the returns of the MSCI World index to calculate PMEs (Column V), or censor the beta in the adjusted PME at unity (Column VI and VII). The rationale behind the latter modification is that portfolio companies of buyout funds are likely to have a higher leverage compared to their public peers. Finally, we replace the PME by the Total Value to Paid-in-Capital (TVPI), which again does not alter our results (Column VIII).[10]

For our measure of portfolio diversification, we present two alternative specifications. As discussed in Section 2.2, we calculate our standard HHI measure from the initial investments in each portfolio company. This approach does not fully reflect the actual portfolio allocations, if a fund's investments in a portfolio company are staged. To address this concern, we recalculate HHIs from the average investment in each company over the funds' lives (denoted as hhiavgComp, hhiavgGeo, hhiavgIndu for the respective concentration measures regarding companies, geographies and industries). Since we cannot distinguish between staged investments and revaluations in our dataset, the downside of this approach is, however, that the diversification measure becomes partly endogenous.[11] While the sign of the respective regression coefficients remains unchanged in all specifications, the coefficients' significance generally increases (to the 5 percent level in the logIRR specifications and to the 10 percent level in the PME specifications). Our last robustness test uses HHIs calculated from geographical diversification at the country, rather than the higher aggregated regional level (denoted as hhiGeoCountry, hhiavgGeoCountry). This modification changes the sign of the geographical

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8 We verify from unreported results that the negative relationship between size and performance is not an artefact from including the diversification variables in the regression.

9 To control for potential heterogeneity in the fund picking abilities of SPFs, we also include LP fixed effects at the level of individual SPFs in our model, and verify that our results are robust against this modification. The results are not reported in order to save on space.

10 We thank two anonymous reviewers for suggesting the latter three modifications.

11 The portfolio weight is a function of the company's return.

diversification coefficient in the logIRR specification, but not in the PME specifications. All coefficients remain statistically insignificant.

4. Conclusions

Based on a hand-collected dataset obtained from Swiss pension funds, we analyze the relationship between diversification in buyout funds' portfolios and fund performance. Unlike most prior studies, which rely on a simple count metric to proxy for diversification, our data allows taking the heterogeneity of initially invested amounts in each portfolio company into account. Moreover, in comparison to earlier research, we control for systematic risk. These innovations have two important ramifications with respect to conclusions drawn in earlier studies on the relationship between diversification and buyout fund performance.

While our results on the relationship of diversification across portfolio companies and performance are generally consistent with results reported by, e.g., Humphery-Jenner (2012, 2013), our findings contradict this earlier evidence on the effect of industry diversification. Specifically, while we find that diversification across portfolio companies is beneficial for fund performance, we document that funds which invest in fewer industries generate higher IRRs.

These findings are well in line with results that have been reported in prior studies on venture capital funds. They provide empirical backing for the hypothesis that the provision of know-how and support, in addition to the investment of capital, forms an important part of the value creation of private equity funds (Hellmann and Puri 2002; Metrick and Yasuda 2011). Our results support the hypothesis of Das et al. (2003), who argue that specialized funds are likely to have a higher level of skills. Such (industry) specialists may therefore take superior investment decisions. Our results suggest that the argument holds for both venture capital, and buyout funds. Regarding geographical diversification, we do not find any statistically significant relationship.

However, our results also suggest that the relationship between industry focus and performance can be partly explained by timing aspects and differences in systematic risk exposure. Using the (beta adjusted) PME as the dependent variable, our results remain qualitatively unchanged, yet, no longer statistically significant, indicating that the performance contribution of a more focused investment strategy is rather modest.

There are several limitations to our study. First, the results we present do not imply any causal relationship, but rather indicate the correlation between diversification and fund performance. Second, compared to prior studies on private equity performance, our sample is relatively small, and the fund investments we observe are sampled from a small number of pension funds, all of which are based in Switzerland. Such a homogeneous group of LP's may have similar preferences for their investments in funds, and potentially have similar fund picking abilities. We therefore acknowledge that the results presented in our study may not represent the population of buyout funds.

These limitations notwithstanding, our findings have implications for practitioners, as a better understanding of the role of fund diversification may allow professional money managers to take superior investment decisions. The advice to investors following from this paper is to select funds that diversify within, but not across industries, while geographical diversification does not seem to be decisive.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Summary of studies on the relationship between diversification and private equity fund performance.

Authors (Year)	Sample/Period	Performance Measure	Diversification Measure	Effect of Diversification on Returns
Cumming and Dai (2010)	1908 VC funds 1980–2009	Exit speed and value growth	Spatial proximity between funds and portfolio company	Spatial focus positive on performance
Cressy et al. (2014)	649 VC funds 1981–2000	Share of companies having reached a successful exit.	HHI of industry and geography	Industry diversification negative Geographical diversification positive
Gompers et al. (2009)	822 VC funds 1975–2003	Success rate of IPO, registration or acquisition, abnormal performance	Specialized funds (HHI)	Specialized funds tend to exit investments more successfully
Humphery-Jenner (2012)	1222 PE funds 1985–2007	IRR Exit multiple	Number of industries and geographies	Industry and geographical diversification positive
Humphery-Jenner (2013)	1505 PE funds 1980–2007	IRR Exit multiple	Number of industries and geographies	Industry and geographical diversification positive
Knill (2009)	1893 VC funds 1998–2006	Probability of exit	Number of geographies, stages, and industries	Beneficial for VC growth, but time to exit delayed
Ljunqvist and Richardson (2003)	73 PE funds 1981–1993	Excess IRR	Number of portfolio companies, % of companies and invested capital in dominant industries, HHI	None
Lossen (2006)	100 PE funds 1979–1998	IRR, MIRR, PME	HHI of industries and geographies	Industry diversification positive Geographical diversification none

Notes: this table presents a summary of studies on the relationship between diversification and private equity fund performance. VC stands for venture capital, PE for private equity, IPO for initial public offering, HHI for Herfindahl–Hirschman Index, IRR for internal return, MIRR for modified internal rate of return, and PME for public market equivalent.

Table A2. Average private equity fund performance.

Authors (Year)	Vintage Years	Mean logIRR	Median logIRR	Mean IRR	Median IRR	Mean PME	Median PME
Higson and Stucke (2012)	1980–2008	0.10	0.09	0.11	0.09	1.22	1.13
Harris et al. (2014)	1984–2008	0.13	0.12	0.14	0.13	1.22	1.16
Phalippou (2014)	1993–2010	n/a	n/a	n/a	n/a	1.20	1.13
Robinson and Sensoy (2016)	1984–2009	0.09	0.09	0.09	0.09	1.19	1.09
This study	1998–2011	0.07	0.07	0.07	0.07	1.22	1.09

Notes: equal weighted averages over all vintage years. The internal rate of return (IRR), its natural logarithm (logIRR), and the Public Market Equivalent (PME) are displayed.

Table A3. Robustness tests (performance measures).

	Dependent Variable							
	logPME		logPME (Beta Adjusted)		PME MSCI	PME (Beta Adjusted, Censored)		TVPI
Independent Variables	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
logComp	0.008		−0.003			0.040		
	(0.88)		(0.96)			(0.65)		
logGeo	0.045		0.048			0.076		
	(0.46)		(0.44)			(0.43)		
logIndu	−0.002		−0.002			−0.109		
	(0.98)		(0.98)			(0.38)		
hhiComp		0.329		0.300	0.515		0.505	0.496
		(0.13)		(0.18)	(0.13)		(0.15)	(0.18)
hhiGeo		0.076		0.052	0.116		0.049	0.103
		(0.53)		(0.68)	(0.54)		(0.80)	(0.61)
hhiIndu		−0.118		−0.126	−0.345		−0.367	−0.355
		(0.45)		(0.43)	(0.15)		(0.14)	(0.18)
logSize	−0.065 **	−0.064 **	−0.064 **	−0.062 **	−0.110 ***	−0.118 ***	−0.105 ***	−0.112 ***
	(0.03)	(0.02)	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Adj. R^2	0.319	0.331	0.347	0.355	0.234	0.288	0.296	0.300

Notes: the table presents ordinary least squares (OLS) estimates of the relation between the natural logarithm of the Public Market Equivalent (logPME), the natural logarithm of the beta adjusted PME (logPME beta adjusted), the PME using MSCI World as a proxy for public market returns (PME MSCI), the beta adjusted PME (PME beta adjusted, censored), which censors the beta for each industry at unity and the Total Value to Paid-in-Capital (TVPI) as the dependent variables and explanatory variables. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *. *p*-values are reported in parentheses. Adj. R^2 refers to the coefficient of determination of the regression. All specifications include vintage year-fixed-effects. The sample consists of 140 buyout funds.

Table A4. Robustness tests (diversification measures).

	Dependent Variable								
	logIRR			PME			PME (Beta Adjusted)		
Independent Variables	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
hhiavgComp	0.582 ***	0.590 ***	0.591 ***	0.565 *	0.561 *	0.498	0.535	0.514	0.438
	(0.00)	(0.00)	(0.00)	(0.10)	(0.10)	(0.16)	(0.14)	(0.15)	(0.23)
hhiavgGeo	0.022			0.052			0.003		
	(0.73)			(0.78)			(0.99)		
hhiavgIndu	−0.177 **	−0.178 **		−0.406 *	−0.418 *		−0.440 *	−0.450 *	
	(0.03)	(0.03)		(0.08)	(0.07)		(0.07)	(0.06)	
hhiavgGeoCountry		−0.009			0.069			0.088	
		(0.85)			(0.61)			(0.54)	
hhiGeoCountry			−0.013			0.071			0.093
			(0.79)			(0.60)			(0.51)
hhiIndu			−0.179 **			-0.345			−0.362
			(0.04)			(0.16)			(0.16)
logSize	−0.128 **	−0.025 *	−0.025 *	−0.100 ***	−0.101 ***	−0.102 ***	−0.097 **	−0.104 ***	−0.106 ***
	(0.05)	(0.06)	(0.07)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Adj. R^2	0.331	0.331	0.329	0.267	0.268	0.261	0.298	0.300	0.292

Notes: this table presents ordinary least square (OLS) estimates of the relation between the natural logarithm of the internal rate of return (logIRR), the Public Market Equivalent (PME) as the dependent variables and explanatory variables. hhiavgComp, hhiavgGeo, hhiavgIndu are the Herfindahl–Hirschman indices (HHI) measuring the concentration of companies, industries, and geographies in a fund based on the average weight over a fund's life. Variables hhiGeoCountry and hhiavgGeoCountry denote the concentration based on countries rather than regions (reported in %). Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *. *p*-values are reported in parentheses. Adj. R^2 refers to the coefficient of determination of the regression. All specifications include vintage year-fixed-effects. The sample consists of 140 buyout funds.

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