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Impact of geographical diversification and limited attention on private equity fund returns

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KEY FINDINGS

- There is a negative correlation between geographical diversification of private equity (PE) funds and PE fund returns.
- PE fund age and industry diversification mitigate the negative correlation between geographical diversification and PE fund returns.
- The relationship between geographical diversification and PE fund returns follows an inverted U shape function, which is consistent with past studies on industry diversification.

ABSTRACT

This article analyzes the effect of geographical diversification on global private equity (PE) fund returns. We find that there is a negative correlation between geographical diversification and PE fund returns. To establish the causality between geographical diversification and PE fund returns, we employ an instrumental variable analysis where the instrument used is the stock market capitalization of the host country where the PE fund is based. Our results apply to Net IRR, TVPI and DPI as dependent variables used to proxy for PE fund returns in the main regression model. A one standard deviation increase in geographical diversification results in an 18.8 percent reduction in PE fund returns from a Net IRR perspective in the main regression model. Fund age and industry diversification mitigate the negative correlation between geographical diversification and fund returns. The relationship between geographical diversification and PE fund returns follows an inverted U shape function. Additional robustness tests further reinforce the findings.

In this article, we examine the effect of the geographical diversification of private equity (PE) funds on PE fund performance returns. We begin our discussion with traditional portfolio theory, where the benefits of portfolio diversification in risk reduction implies that a fund manager would hold a portfolio of diversified assets to obtain the optimal risk and return trade-offs. Sharpe (1964) developed the capital asset pricing model (CAPM) where investors are only compensated for assuming systematic risk which cannot be diversified away. Ross (1976) added refinements to the CAPM model through the introduction of the arbitrage pricing theory (APT) model which advocates that investors should be fully diversified except for the exposure to systematic or non-diversifiable risks in their portfolios. Markowitz (1970) demonstrated that portfolio diversification results in risk reduction of the overall portfolio and a shift of the risk return combination in portfolios towards what is known as the efficient frontier until the market portfolio is observed. Established finance theory assumes investors to have fully diversified asset portfolios. However, in PE investments, focus or concentration is essential for implementing value creation initiatives that enable PE funds to obtain higher portfolio valuations, effect successful deal exits and achieve targeted returns. PE fund managers or General Partners (GPs) can potentially be impacted by the limited attention issue which has been observed to affect hedge fund managers, liquidity traders and mutual fund managers in past studies.

We will explore whether geographical diversification has a negative correlation with PE fund returns and apply a diversification discount to those returns. Previous studies do not sufficiently explore this aspect of PE and have focus on industry diversification. The results of our empirical findings will have important industry ramifications. PE GPs must make decisions about whether their investments and fundraising efforts should focus on one or multiple geographic areas. Those decisions affect funds' recruitment efforts, as recruiting PE professionals who have either specific or diverse geographical expertise is critical to supporting a fund's investment strategy.

Our empirical findings show that PE funds that invest in multiple geographical locations can suffer from limited attention issues and experience adverse impacts on their returns compared to funds that invest in a single location. We also identify certain attributes of PE funds, for example fund age and industry diversification that mitigate or weaken the adverse impact of geographical diversification on returns. Finally, we show that the relationship between geographical diversification and PE fund returns follows an inverted U-shaped function, in which excessive diversification has an adverse effect on returns after an inflexion point. We use a global PE fund data set as compared to previous studies that have used North American or European PE data sets. Past studies on PE diversification also provides limited or no discussion of endogeneity issues, a perceived weakness which our paper will address by incorporating endogeneity treatment methods.

The remainder of this article is organized as follows. The next section discusses the relevant literature on PE diversification, PE fund age and performance as well as limited attention issues in other asset classes. After that we discuss our research hypotheses, data and methodology. The following sections highlight our study findings, describe robustness tests and discuss alternative explanations. The final section concludes this article and discusses possible areas for future research.

LITERATURE REVIEW

Several past studies have examined the relationship between diversification and PE returns. Most of these studies find either a positive relationship between diversification and PE returns or provide no conclusive findings in contrast to the empirical findings from this article. Humphery-Jenner (2013) finds that PE returns improve with diversification, and the positive correlation between diversification and PE returns is linked to the benefits of information sharing. Although that study does not provide any conclusive findings on the effect of geographical diversification on PE returns, it does find that regional diversification has a positive impact on the performance of seed funds, as evidenced from their higher internal rates of return (IRRs). Extensive industry diversification stretches resources and causes limited attention issues that attenuate PE returns. Alternative explanations for the positive effects of diversification on PE returns are linked to a reduction in firm-specific risks and a greater willingness to pursue higher-risk investments. Well-diversified PE funds avoid low-risk and mediocre investment prospects for which they lack internal knowledge. There is a need to incorporate a risk element when assessing the impact of geographical diversification and this article will include risk adjusted performance metrics.

Lossen (2006) reports that the returns of PE funds decrease across financing rounds but increase across different industries. Significantly, that study finds no conclusive evidence of the impact of geographical diversification on PE fund returns. Cressy, Munari, and Malipiero (2007) study PE buyout transactions using a sample of UK firms and find that PE-backed firms that specialise in a single industry and are at similar funding stages outperform their peer firms that do not specialise. Huss and Steger (2020) posit that diversification within industries helps PE returns, whereas diversification across industries does not. They find that geographical diversification has no significant effect on buyout returns. One limitation of their study is that their sample consists of fewer than 200 PE funds from the portfolio holdings of Swiss pension funds. Bowden, Harjoto, Paglia, and Tribbitt (2016) analyse a sample of US PE funds and find that both industry or sector diversification and geographical diversification have a positive impact on PE returns, especially during periods of strong economic performance. We note that previous studies on PE diversification (Lossen, 2006; Cressy et al. 2012; Humphery-Jenner 2013; Bowden et al. 2016; Huss and Steger 2020) do not explore the involvement of other variables that may mitigate the effects of geographical diversification on PE fund returns. This is a research gap that we will address in this article through empirical methods and multivariate regression analysis.

A number of past studies have also looked at venture capital (VC) diversification and discuss the benefits of specialisation in the context of VC investments. Gompers, Kovner, and Lerner (2009) find that specialist VC firms tend to outperform generalist VC firms that do not focus on specific areas or sectors. Gupta and Sapienza (1992) posit that VC funds that invest in early-stage ventures have less industry and geographical diversification, and that corporate VC funds have less industry diversification but more geographical coverage. Norton and Tenenbaum (1993) provide evidence of the benefits of information sharing.

Knill (2009) finds that increasing international diversification has a positive impact on VC firm growth. That study's model uses VC firm growth as a dependent variable, which is not an established performance metric in PE funds, such as Net IRR, total value over paid-in (TVPI) or distributions over paid-in capital (DPI). Cressy, Malipiero, and Munari (2012) in a study of VC funds in the UK find that geographical diversification by country has a positive impact on the success of VC funds, whereas excessive industry diversification has an adverse impact. They use Net IRR as the dependent variable, in contrast to the VC firm growth variable used by Knill (2009). Bucher, Mohamed, and Schwienbacher (2017) note that diversified VC funds with lower risk profiles pursue higher-risk transactions that generate higher expected returns. Matusik and Fitza (2012) argue that VC firms benefit from either high or low levels of diversification due to processing efficiencies or diverse information sources that enable complex problem solving.

A few studies have look at the relationship between PE fund age and performance which we will also examine in this article. Gompers (1996) argues that new PE funds have a higher propensity to take risks at an early stage to develop their brand and reputation. Gompers, Kovner, Lerner, and Scharfstein (2008) posit that more experienced funds have an advantage because they can make superior investment decisions in changing public market conditions without impacting performance. Giot, Hege, and Schwienbacher (2014) find that new and inexperienced funds tend to invest more slowly than experienced funds, but the size of the newer funds' investments is larger. Newer funds underperform compared to their more established peers, and this performance shortfall is particularly significant for larger investments. Ljungqvist, Richardson, and Wolfenzon (2019) find that older and more experienced funds can increase the pace of their investments whenever market conditions improve.

From these studies, fund age can be a factor which may mitigate the adverse effects that geographical diversification may have on PE performance.

Limited attention issues have been observed in past studies of hedge fund performance, mutual funds and in publicly listed exchanges. Lu, Ray, and Teo (2015) show that a hedge fund manager's marriage and divorce are both associated with the deterioration of risk-adjusted performance. The hedge fund performance alpha falls by 8.50% per annum in the 6-month period surrounding marriage and falls by 7.39% per annum in the same window surrounding divorce. Corwin and Coughenour (2008) observe that liquidity traders experience limited attention issues in publicly listed stock markets, as they focus more on actively traded stocks than on thinly traded stocks when they monitor larger portfolios. Peng and Xiong (2006) observe that investors tend to focus on market- and sector-specific information instead of company-specific information when impacted by limited attention, leading to investor overconfidence that results in asset price movements inconsistent with rational expectation models. Mukherjee and Pareek (2020) posit that limited attention impacts mutual fund managers' ability to efficiently allocate their task focus when taking asset positions that require information-acquisition efforts. Zhang and Wang (2015) observe that investors' limited attention impacts performance in China's ChiNext market. These findings provide an opportunity for our paper to explore the impact of limited attention on PE funds that pursue geographical diversification and if this results in adverse effects on PE fund returns.

HYPOTHESES, DATA AND METHODOLOGY

We find a gap in prior research on the relationship between geographical diversification and its impact on PE returns. Studies have instead focused on the effect of industry diversification on PE returns, with geographical diversification having a secondary role.

Past studies allude to the benefits of diversified industry expertise. Humphery-Jenner (2013) and Lossen (2006) find that industry diversification by PE and VC funds has a positive impact on returns and that industry expertise is an attribute valued by general partners (GPs) in staff recruitment. Studies by Huss and Steger (2020) and Bowden, Harjoto, Paglia, and Tribbitt (2016) allude to the benefits of industry diversification on PE performance and returns. Understanding the role that diverse industry expertise can have on the impact of geographical diversification will provide useful insights for the PE industry if diverse industry expertise in PE firms can attenuate the impact of limited attention associated with geographical diversification. This is intuitive, as the industry concentration of private firms available for PE investment will be different in various geographical locations, and PE funds with heterogenous industry knowledge will be in an advantageous position vis-à-vis PE funds without this knowledge. In a 2014 study, Cambridge Associates found that PE funds with deep industry or sector expertise in the consumer sector, financial services, health care and technology generate superior returns compared to other peer comparison groups.[1] Bain (2021) mentions in a 2021 private equity report[2] that PE firms require industry intelligence or sector expertise to take advantage of changes in industry trends during an economic recovery phase, especially in the post-COVID-19 pandemic era. PE funds with diverse industry expertise may thus be able to mitigate the adverse effects of geographical diversification.

[1] Declaring a major: sector-focused private investment funds: Cambridge associates research September 2014.

[2] Bain 2021 Global private equity report Pg 8 https://www.bain.com/globalassets/noindex/2021/bain_report_2021-global-private-equity-report.pdf.

Humphery-Jenner (2013) refers to an inverted U shape function for the relationship between industry diversification and PE returns, where some industry diversification is beneficial for PE returns due to knowledge sharing but excessive industry diversification has an adverse impact on PE returns after an inflexion point. We will evaluate whether an inverted U-shaped relationship also exists for geographical diversification and PE fund returns.

Based on the above and review of the prior literature, we propose the following hypotheses:

> **H1**: *PE fund returns are negatively correlated with geographical diversification, and there is a diversification discount for PE funds pursuing geographical diversification.*
>
> **H2**: *The negative correlation between PE fund returns and geographical diversification is mitigated or weakened by PE fund age.*
>
> **H3**: *The negative correlation between PE fund returns and geographical diversification is mitigated or weakened by the industry diversification of the PE fund.*
>
> **H4**: *The relationship between PE fund returns and geographical diversification will follow an inverted U shape function.*

We use a baseline multivariate regression model with independent variables and controls and the full multivariate regression model that will incorporate both the independent variables, interaction variables and controls, which will be known as the main regression model in the study. We will utilize the main regression model to evaluate research hypotheses one to three (H1, H2 and H3) but will also discuss findings from the baseline regression model.

The baseline regression model is as follows:

$$\begin{aligned} Y_i = {} & constant + X_1(country_{count}) + X_2(\ln fund\ size) + X_3(fund\ age) \\ & + X_4(top\ quartile\ performance\ classification) + X_5(diverse\ industry) + \varepsilon \end{aligned} \tag{1}$$

where $X_1(country_{count})$ is the main effect independent variable that will proxy for the effect of geographical diversification in PE funds, and X_2, X_3 and X_4 are the independent and control variables for fund size, fund age, and top quartile PE performance, respectively. Top quartile performance relates to the quartile one ranking of the funds in the data sample of the study classified by Preqin.[3] X_5 is a control variable that is a dummy variable to identify whether PE funds have diversified industry investments or are focused on only specific industries such as information technology or semiconductor chip production.

The main regression model that will be used to support the proposed research Hypotheses H1 to H3 is as follows:

$$\begin{aligned} Y_i = {} & constant + X_1(country_{count}) + X_2(\ln fund\ size) + X_3(fund\ age) \\ & + X_4(top\ quartile\ performance\ classification) + X_5(diverse\ industry) \\ & + X_6(fund\ age \times country_{count}) + X_7(diverse\ industry \times country_{count}) + \varepsilon \end{aligned} \tag{2}$$

[3]When calculating the quartile ranking, Preqin puts equal weight on IRR and multiple. It has specific benchmarks for buyout, venture, early stage, fund of funds, real estate and mezzanine funds. Funds of a different type are benchmarked against "All Private Equity". Top quartile funds are funds with an IRR or multiple equal to or above the upper quartile benchmark; second quartile funds are funds with an IRR or multiple equal to or above the median quartile figures but under the upper quartile figures (Source: Preqin data definitions).

where Y_i is the performance return of PE funds proxied by the dependent variable of Net IRR, TVPI (Total value over paid-in) and DPI (Distributions over paid-in).

$X_1(country_{count})$ is the main effect independent variable that will proxy for the effect of geographical diversification on PE funds, and X_2, X_3 and X_4 are the independent and control variables for fund size, fund age and top quartile PE performance, respectively. X_5 is a control variable that is a dummy variable to identify PE funds having diversified industry investments or are focusing on only specific industries such as the semiconductor industry or information technology.

X_6 is the variable for the interaction effect of fund age and geographical diversification, and X_7 is the variable for the interaction effect of industry diversification and geographical diversification in PE funds.

We have controlled for different fund strategies, different geographical regions fixed effects (developed and emerging markets) and year fixed effects in the regression models. We use the control variable "Region" to control for potential performance returns difference in PE funds operating in developed regions and emerging regions. This is done in reference to Nahata, Hazarika, and Tandon (2014) who mention that differences in legal protection and stock market development in different countries can impact venture capital investments in their studies of VC investments in 30 countries. Lerner, Ledbetter, Speen, Leamon, and Allen (2016) show differences in exit opportunities for funds investing in developed and emerging markets. The regression model controls for years' fixed effects due to different cyclical and economic conditions which may impact PE returns during the different vintage years of the PE funds in the study sample.

To study hypothesis four (H4), we utilize the baseline regression model, which includes a quadratic function of the main effect geographical diversification variable (country count), which is classified as (country count^2) in the regression model.

The multivariate regression model to evaluate hypothesis four (H4) will be as follows:

$$\begin{aligned} Y_i = {} & constant + X_1(country_{count}) + X_2(country^2_{count}) + X_3(\ln fund\ \ size) + X_4(fund\ \ age) \\ & + X_5(top\ \ quartile\ \ performance\ \ classification) + X_6(diverse\ \ industry) + \varepsilon \end{aligned} \tag{3}$$

A separate OLS multivariate regression analysis will reinforce support for hypothesis four (H4). To demonstrate that the relationship between geographical diversification and PE fund returns follows an inverted U shape function, the analysis will show a positive and significant coefficient for the country count variable and a negative and significant coefficient for the quadratic function (country count^2 variable). All regression models will have controls for region fixed effects, year fixed effects and fund strategy fixed effects.

The data for the research study have been obtained primarily from Preqin's private equity database. The study uses three different performance metrics, Net IRR, Total value over paid-in (TVPI) and Distributions over paid-in (DPI). Due to shortcomings associated with the reinvestment assumption for Net IRR, the study results obtained using DPI and TVPI will be prioritized, as these two metrics have gained traction and acceptance in industry and academia. We review histogram charts of the dependent variables as shown in the Appendix and apply natural log treatments to the dependent variables to ensure normality of the dependent variables' distributions. In addition, we also assess a case of no natural log treatments for DPI and TVPI with the regression results in this case showing similar findings to the case when natural log treatments are applied to DPI and TVPI.

A critical aspect of data collection is to ensure that there are adequate observations in the sample set. The study will have approximately 8,000 sample observations of PE funds for multivariate regression analysis. Fund vintages are obtained from 1973 to 2018 with the assessment year in 2019 to measure PE fund returns. Data are available showing the different geographical locations that PE funds are investing in. These data are crucial in the development of the country count variable (country count), which is the main independent variable that proxies for the relationship between geographical diversification and PE fund returns. The country count variable (country count) will track the number of geographical locations that PE funds in the sample dataset will invest into. The extent of the geographical diversification in PE funds can thus be assessed in the study.

The dataset will include industry diversification data of PE funds investing either in a single industry or multiple industries. The availability of industry diversification and fund age data will enable us to assess whether there are mitigating effects from fund age and industry diversification on the adverse impact of geographical diversification on PE fund performance.

Sample Descriptive Statistics

The summary descriptive statistics highlight the differences in fund attributes and performance between PE funds that invest in one geographical location (single geographic PE funds) and PE funds that invest in multiple geographical locations (multi-geographic PE funds). Multi-geographic PE funds invest in more than 3 geographical locations. Geographical locations that include countries such as Australia and New Zealand are often categorized into one location, and this is also seen for cases that include Hong Kong, Macau, and mainland China. For the analysis, we thus define a multi-geographic PE fund as one that invests in more than 3 geographical locations. The summary descriptive statistics are illustrated in Exhibit 1, Panels A to M.

EXHIBIT 1

Summary Descriptive Statistics

	Panel A: Independent Variable: Fund Age		Panel B: Independent Variable: Fund Size		Panel C: Independent Variable: Country Count		Panel D: Independent Variable: Top Quartile	
Descriptive Statistic	Single	Multi	Single	Multi	Single	Multi	Single	Multi
N	7,736.00	592.00	7,241.00	568.00	7,750.00	592.00	7,750.00	592.00
Mean	11.41	9.71	924.91	1,148.21	1.00	6.27	0.24	0.28
Standard Deviation	7.92	6.80	2,516.87	1,615.53	0.00	3.08	0.43	0.45
25th Percentile	5.00	4.00	120.00	178.11	1.00	4.00	0.00	0.00
50th Percentile	11.00	8.00	300.00	474.38	1.00	6.00	0.00	0.00
75th Percentile	17.00	13.50	750.00	1,548.82	1.00	7.00	0.00	1.00

	Panel E: Dependent Variable: TVPI		Panel F: Dependent Variable: DPI		Panel G: Dependent Variable: Net IRR	
Descriptive Statistic	Single	Multi	Single	Multi	Single	Multi
N	7,557.00	576.00	7,628.00	582.00	6,305.00	464.00
Mean	1.67	1.60	111.67	100.90	16.19	16.10
Standard Deviation	1.28	0.75	112.96	99.65	32.82	14.84
25th Percentile	1.19	1.17	23.28	13.46	7.67	7.29
50th Percentile	1.50	1.44	105.20	82.00	13.00	13.12
75th Percentile	1.87	1.85	159.96	152.54	20.20	20.00

(continued)

EXHIBIT 1 *(continued)*

Summary Descriptive Statistics

	Panel H: TVPI			Panel I: DPI			Panel J: Net IRR		
Descriptive Statistic	Buyout Funds	Growth or Pre-IPO	Fund of Funds	Buyout Funds	Growth or Pre-IPO	Fund of Funds	Buyout Funds	Growth or Pre-IPO	Fund of Funds
N	4,225.00	994.00	2,354.00	4,263.00	1,004.00	2,386.00	3,574.00	736.00	2,001.00
Mean	1.73	1.62	1.56	130.64	91.63	90.08	16.50	15.76	11.65
Standard Deviation	1.08	1.12	0.60	127.26	122.10	79.34	19.52	22.80	8.51
25th Percentile	1.17	1.03	1.23	36.32	3.65	19.83	8.00	12.98	7.06
50th Percentile	1.56	1.40	1.48	123.80	50.00	90.46	14.10	20.77	10.70
75th Percentile	2.06	1.90	1.74	188.20	144.21	135.00	22.91	7.42	15.01

	Panel K: Buyout Funds Strategy				Panel L: Growth Funds Strategy			
Descriptive Statistic	Single	Multi	Single	Multi	Single	Multi	Single	Multi
N	3,309.00	342.00	3,339.00	80.00	344.00	780.00	82.00	786.00
Mean	1.73	1.62	131.73	1.51	111.46	1.60	71.39	91.21
Standard Deviation	1.13	0.77	131.33	0.89	104.67	1.08	103.28	120.24
25th Percentile	1.15	1.17	38.70	1.00	14.58	1.04	4.33	2.46
50th Percentile	1.56	1.47	122.92	1.35	108.00	1.41	44.11	51.04
75th Percentile	2.07	1.98	189.00	1.70	170.40	1.90	85.80	146.47

	Panel M: Fund of Funds Strategy			
Descriptive Statistic	Single	Multi	Single	Multi
N	96.00	2,134.00	2,162.00	96.00
Mean	1.60	1.56	91.84	77.05
Standard Deviation	0.50	0.61	80.71	61.89
25th Percentile	1.32	1.23	20.30	23.20
50th Percentile	1.49	1.48	94.18	78.36
75th Percentile	1.68	1.74	136.32	123.45

NOTES: This exhibit reports the summary descriptive statistics of the fund age profile of single geographic PE funds and multigeographic PE funds. The PE funds have vintage years from 1973 to 2018. Panel A: Only PE funds are studied in the sample, and fund age is obtained by calculating the number of years from the vintage year of the fund to the assessment year, which is 2019. There is no lognormal distribution treatment applied to the fund age data. Panel B: Only PE funds are studied in the sample, and fund size is obtained in US dollars at the final closing of the PE funds by the GPs of the fund. The summary descriptive statistics for fund size do not include any natural logarithm being applied. Panel C: Country count (Country count) is obtained by determining the number of geographical locations that the PE fund invests in based on the overall sample of PE funds in the study. Panel D: The top quartile variable is obtained by allocating a dummy variable to quartile 1 fund performance according to the quartile 1 classification by Preqin. Panel E: Only PE funds are studied in the sample, and the TVPI is calculated by taking the exit proceeds of the PE fund returned to investors or limited partners (LPs) over the initial investment of the LPs. Panel F: Only PE funds are studied in the sample, and the DPI is an index calculated by taking the present value of cash flow distributions from the GPs to the LPs over the initial investment provided by the LPs to the PE funds. Panel G: Only PE funds are studied in the sample, and the Net IRR used as a performance measure by Preqin considers both the management fees and the performance fee or carried interest charged by the GPs to the LPs.

This exhibit panels H, I and J reports the summary descriptive statistics of the performance of PE funds pursuing buyout, growth or pre-IPO and fund of funds strategies. The PE funds have vintage years from 1973 to 2018. The summary statistics are based on the full sample of PE funds pursuing these three strategies, and the performance metrics used are the TVPI (total value over paid-in), DPI (distributions over paid-in) and Net IRR, which has been calculated net of all GP fees. The year of assessment for the PE funds' performance is 2019.

These panels K, L and M show the performance of single geographic funds versus multigeographic funds when using the buyout, growth and fund of funds strategies. Fund vintages are taken from 1973 to 2018, and the assessment year for return calculations is 2019. Single geographic funds refer to funds that invest in a single geographical location, whereas multigeographic funds refer to funds that invest in three or more geographic locations. The performance metrics used are the TVPI(total value over paid-in) and DPI (distributions over paid-in).

SOURCE: Preqin's PE database.

EXHIBIT 2

Fund Performance Using DPI as the Dependent Variable

PE Fund Group	Observation	Mean	Std. Error	Std. Dev.	[95% Confidence Interval]	
Single Geographic (0)	7,628	111.6668	1.293368	112.9607	109.131400	114.20210
Multigeographic (1)	582	100.8964	4.130480	99.6465	92.783900	109.00890
Diff [Mean(0)–Mean(1)]		10.7704	4.819240		1.323109	20.21769
Student's *t*-statistic	$t = 2.2348$					
Degrees of Freedom	8,208					

The summary descriptive statistics in Panels A and B illustrate that single geographic PE funds are older than multi-geographic PE funds, with the mean fund age of single geographic PE funds being 2 years older than that of multi-geographic PE funds. At the 75th percentile level, the difference is even more discerning, with single geographic PE funds being 3.5 years older than multi-geographic PE funds. In terms of fund size, Panel B shows that multi-geographic PE funds are larger compared to single geographic PE funds, with the mean fund size of single geographic PE funds being USD 924.1 million compared to USD 1.1 billion for multi-geographic PE funds. The difference in fund size is more evident at the 75th percentile level, with multi-geographic PE funds being twice as large at approximately USD 1.5 billion compared to single geographic PE funds at USD 750 million.

The summary descriptive statistics presented in Panels C and D show the distribution of the country count variable (country count) and the top quartile classification variable. The median multi-geographic PE funds in 6 different locations show that the median funds in the sample that have a multi-geographic strategy are pursuing extensive geographical diversification. The summary descriptive statistics presented in Panels E, F, and G show that single geographic PE funds outperform multi-geographic PE funds based on all 3 dependent variables to proxy for PE fund returns, and the results are most evident when DPI is used as a performance metric. Mean statistics for all 3 dependent variables used to proxy for PE performance show that single geographic PE funds perform favorably compared to multi-geographic PE funds.

The data in Exhibit 2 show the difference in the mean DPI of the single geographic PE funds and multi-geographic PE funds. We show a nonparametric student's *t*-test of means to ascertain the difference in performance between the two groups of PE funds.

The difference in the mean DPI statistic between the two groups is significant at the 5 percent level with a *t*-statistic of 2.2348 for a one-tailed *t*-statistic test. This result provides evidence that geographical diversification in PE funds can adversely impact PE fund returns.

Summary Descriptive Statistics of PE Fund Strategies

The three major PE fund strategies included in the study that are considered important strategies for PE fund managers of GPs are buyouts, growth funds and Fund of funds strategies. These PE strategies differ in terms of the extent of PE involvement required in portfolio investments. Panels H, I and J in Exhibit 1 illustrate the summary statistics of the three different PE fund strategies using the performance metrics, which include TVPI (total value over paid-in), DPI (distributions over paid-in), and Net IRR (internal rate of return).

Analyzing the summary statistics, buyout PE fund strategies outperform both growth and fund of funds strategies using all three PE performance metrics of TVPI, DPI and net IRR. The difference in performance is most evident when using DPI as a performance metric, with mean DPI of buyout funds at 130.64 being superior to the mean DPI of growth funds at 91.63 as well as the mean DPI for Fund of funds which stands at 90.08. When using Net IRR as a metric, the performance edge that buyout PE funds has over the other strategies does not seem significantly large, with a mean IRR of 16.50 compared to the mean IRR of 15.76 for growth funds and 11.65 for fund of funds. The fund of funds PE fund strategies show the lowest performance figures compared to the other two strategies.

We review Panels K, L, and M in Exhibit 1, which illustrate the summary descriptive statistics of the performance metrics of the strategies of buyouts, growth and fund of funds that are either single geographic PE funds or multi-geographic PE funds. Single geographic buyout PE funds outperform multi-geographic buyout funds both on a TVPI and DPI basis, with single geographic buyout funds achieving a mean TVPI of 1.73 versus a mean TVPI of 1.62 for multi-geographic buyout PE funds. The difference in performance on a DPI basis is even more evident, with single geographic buyout PE funds achieving a mean DPI of 131.73 compared to 111.46 for multi-geographic buyout PE funds. Single geographic growth funds outperform multi-geographic growth funds both from a TVPI and DPI performance metric basis. PE funds pursuing fund of funds strategy, however, deviate slightly from the pattern with multi-geographic fund of funds outperforming single geographic fund of funds using TVPI as a performance metric. However, using DPI, a single geographic fund of funds outperforms multi-geographic fund of funds, achieving a mean DPI of 91.84 versus 77.05 for multi-geographic fund of funds. The varying performance of different fund strategies thus need to be controlled in multivariate regression models, which we will use in the study.

EXHIBIT 3A

Multivariate Regression on the Impact of Geographical Diversification on PE Returns with Specific Independent Variables and Controls

Independent Variable	Dependent Variable Being Studied		
	Net IRR	Log (TVPI)	Log (DPI)
Country Count	–0.016	–0.004**	–0.029**
	(–0.16)	(–2.94)	(–2.99)
Log (fund size)	–0.914**	–0.001**	0.031**
	(–6.58)	(–5.14)	(4.24)
Fund Age	1.381**	0.027**	0.022**
	(3.40)	(7.83)	(10.81)
Top Quartile	18.212**	0.30**	0.694**
	(27.45)	(56.33)	(32.86)
Diverse Industry	–0.314	0.019**	0.177**
	(–0.38)	(3.37)	(6.49)
Region	0.690	0.022**	0.166**
	(1.01)	(2.81)	(4.45)
Strategy Fixed Effects	Yes	Yes	Yes
Years Fixed Effects	Yes	Yes	Yes
R-Squared	0.181	0.475	0.742
N	7,154	8,479	8,563

NOTES: This exhibit reports coefficient estimates from multivariate regressions on global PE fund returns, which are impacted by geographical diversification of the funds' investment returns. The *t*-statistics, derived from robust standard errors clustered by fund, are in parentheses. * significant at the 5% level; ** significant at the 1% level.

FINDINGS AND DISCUSSION

The figures in Exhibit 3A show negative coefficients for the country count variable (country count), which proxies for geographical diversification for all three dependent variables, which indicates that there is a negative correlation between geographical diversification and PE fund returns. These findings are significant at the 1 percent significance level for TVPI (t stat = –2.94) and DPI (t stat = –2.99).

There is a positive correlation between fund age and PE fund returns, which highlights that established and experienced PE funds outperform less experienced PE funds. The findings are pervasive across all 3 dependent variables and significant at the 1 percent level (Net IRR: t stat = 3.40, TVPI: t stat = 7.83, and DPI: t stat = 10.81). There is also evidence that industry diversification by PE funds has a significant impact on PE fund returns, as seen from the positive coefficients of the diverse industry variable and the significant t statistics for TVPI (t stat = 3.37) and DPI (t stat = 6.49) at the 1 percent significance level. These results further reinforce past findings from Humphery-Jenner (2013), Lossen (2006), Bowden et al. (2016) and Huss and Steger (2020) on the positive impact that diverse

EXHIBIT 3B

Multivariate Regression on the Impact of Geographical Diversification on PE Returns with Specific Independent Variables and Controls

	Dependent Variable Being Studied		
Independent Variable	**Net IRR**	**Log (TVPI)**	**Log (DPI)**
Country Count	–0.981**	–0.012**	–0.062**
	(–2.92)	(–2.68)	(–2.68)
Log (fund size)	–0.904**	–0.010**	0.030**
	(–6.53)	(–5.19)	(4.19)
Fund Age	1.271**	0.027**	0.213**
	(3.09)	(7.65)	(10.70)
Top Quartile	18.163**	0.299**	0.693**
	(27.45)	(56.27)	(32.74)
Diverse Industry	–0.501	0.007	0.130**
	(–0.43)	(1.01)	(3.16)
Fund age x Country Count	0.083**	0.0002	0.001
	(3.01)	(0.97)	(0.89)
Diverse Industry x Country Count	0.174	0.008**	0.032
	(0.45)	(2.63)	(1.43)
Region	0.784	0.023**	0.170**
	(1.14)	(2.92)	(4.58)
Strategy Fixed Effects	Yes	Yes	Yes
Years Fixed Effects	Yes	Yes	Yes
R-Squared	0.182	0.475	0.742
N	7,154	8,479	8,563

NOTES: This exhibit reports coefficient estimates from multivariate regressions on global PE fund returns, which are impacted by geographical diversification on the funds' investment returns. The t-statistics, derived from robust standard errors clustered by fund, are in parentheses. * significant at the 5% level; ** significant at the 1% level.

industry expertise in PE funds have on returns. Industry diversification, unlike geographical diversification, has a positive impact on PE fund returns, which may be attributable to both lower costs and greater benefits for PE funds in having diversified industry investments compared to being geographically diversified.

The regression results show negative coefficients for fund size and is significant at the 1 percent level for Net IRR and TVPI. The inverse relationship between PE fund size and returns seen in past studies has been referred to as a scale diseconomy issue in PE funds. Humphery-Jenner (2012) posit that large PE funds should generate lower returns than small PE funds especially when they invest outside of their area of expertise and in smaller scale investments. One of the reasons cited by the study is that smaller PE funds because of their lower cost structures and fixed costs are less prone to agency issues compared to larger PE funds. Marquez, Nanda and Yavuz (2014) find that PE fund managers keep fund sizes small due to the effort needed to attract superior performing entrepreneurs to accept PE investment. Cumming and Dai (2010) study VC funding valuation data in the US and find a convex relationship between fund size and the valuation of the portfolio companies after controlling for portfolio attributes, reputation and market conditions. The authors attribute this observation to larger funds being impacted by the limited attention issue which results in overpaying for transactions.

The results in our multivariate regression analysis also show a positive coefficient for fund size for DPI and significant at the 1 percent level. A possible explanation for the positive relationship between fund size and DPI can be that larger funds are deemed to be less risky and have some advantages in obtaining competitive financing terms compared to small funds (Hochberg, Ljungqvist, and Lu, 2007; Hellman, Lindsey and Puri, 2008). Humphery-Jenner (2012) also mentions that large funds generate better returns when investing in larger companies compared to cases when these funds are investing in smaller companies. The DPI measure may not have captured the adverse effects in the studies by Humphery-Jenner (2012) and Cumming and Dai (2010) which mentions the inverse relationship between portfolio valuation and fund size as it focuses only on the cash flow distributions of the fund which occurs at the latter period of the fund life.

The results from the main multivariate regression model shown in Exhibit 3B suggest that there is a negative correlation between geographical diversification as proxied by the main effect country count variable (country count) and PE fund returns as proxied by the dependent variables used, which are the Net IRR, TVPI, and DPI.

The main effect country count variable (country count), which proxies for geographical diversification in the regression analysis, shows negative coefficients, and the results are significant at the 1 percent level for all 3 dependent variables, as shown by the student's t statistics: IRR (*t* stat = –2.92), TVPI (*t* stat = –4.78), and DPI (*t* stat = –2.68). This finding supports hypothesis one (H1) in the study that there is a negative correlation between geographical diversification and PE fund returns and that there is a diversification discount for PE funds pursuing geographical diversification. The results for the main effect independent variable for geographical diversification (country count) are thus consistent with the findings of the baseline regression model in Exhibit 3A. In addition, referencing country count summary descriptive statistics from Panel C, mean IRR data from Panel G and the main regression model output in Exhibit 3B in the appendix, a one standard deviation increase in geographical diversification proxied by country count is associated with an 18.8 percent reduction in PE fund returns from a Net IRR perspective. This is obtained by using the following calculation: standard deviation of country count of multi geographic funds * coefficient of country count/mean of multi geographic fund Net IRR. This provides the following result after making the calculations: 3.08 * (–0.981)/16.10 = –18.8%. For TVPI, due to the natural log treatment of the dependent variable, I apply the following calculation: [Exp (0.012)-1] * 100 * 3.08 = 3.72 percent. The methodology for the calculation is taken from a past publication from UCLA.[4]

A control variable that is a diverse industry variable that proxies for industry diversification has a positive coefficient and is significant at the 1 percent level for DPI (t stat = 3.16) and shows a positive coefficient for TVPI. This supports the earlier findings of Lossen (2006), Humphery-Jenner (2013), Huss and Steger (2020) and Bowden et al. (2016), reinforcing that PE returns increase as PE funds have diverse industry or sector expertise.

The regression analysis reveals insights involving the interaction variables in the model, which supports hypotheses two (H2) and three (H3) in the study. The interaction variable of fund age and country count (fund age × country count) indicates a positive coefficient and is significant at the 1 percent level for Net IRR (t stat = 3.01). This finding demonstrates that older, established and more experienced PE funds can handle the limited attention issue of pursuing geographical diversification efforts. This finding thus supports hypothesis two (H2), which states that the negative correlation between PE fund returns and geographical diversification is mitigated or weakened by PE fund age. The regression model also provides further insight into the interaction variable of diverse industry and country count (diverse industry × country count), which assesses the interaction of industry diversification and geographical diversification of PE funds. This interaction variable has a positive coefficient and is significant at the 1 percent level (t stat = 2.63) for TVPI. PE funds with industry diversification in their investments or with diverse industry expertise are better able to cope with the limited attention issue when pursuing geographical diversification. This provides intuitive reasoning, as PE funds with only expertise in one industry, for example, in the semiconductor chip segment, will find it difficult to expand their geographical exposure from markets such as Taiwan and Korea that have a significant presence in the semiconductor industries to countries in the Southeast Asia region. This supports hypothesis three (H3), which states that the negative correlation between PE fund returns and geographical diversification is mitigated by the industry diversification of PE funds. The main regression model also shows negative coefficients for fund size and significant at the 1 percent level for Net IRR and TVPI but positive coefficients for fund size and significant at the 1 percent level for DPI similar to the baseline multivariate regression model in Exhibit 3A.

To assess Hypothesis 4 (H4), we use additional regression analysis based on the multivariate regression model results presented in Exhibit 3C in the appendix.

For geographical diversification to have an inverted U shape function with PE fund returns where geographical diversification will reach an inflexion point and thereafter have a negative correlation with PE fund returns, we will need to obtain a positive coefficient with a significant t statistic for country count and a negative coefficient with

[4] https://stats.idre.ucla.edu/sas/faq/how-can-i-interpret-log-transformed-variables-in-terms-of-percent-change-in-linear-regression/.

EXHIBIT 3C

Multivariate Regression on the Impact of Geographical Diversification Incorporating a Quadratic Function

	Dependent Variable Being Studied		
Independent Variable	Net IRR	Log (TVPI)	Log (DPI)
Country Count	0.367	0.004	0.034**
	(1.48)	(1.43)	(2.56)
Country Count^2	–0.033*	–0.001**	–0.005**
	(–2.07)	(–3.82)	(–5.44)
Log (fund size)	–0.921**	–0.010**	0.030**
	(–6.62)	(–5.22)	(4.08)
Fund Age	1.373**	0.027**	0.214**
	(3.37)	(7.78)	(10.76)
Top Quartile	18.209**	0.299**	0.693**
	(27.45)	(56.37)	(32.88)
Diverse Industry	–0.327	0.019**	0.171
	(–0.40)	(3.25)	(6.30)
Region	0.816	0.025**	0.191
	(1.17)	(3.18)	(5.14)
Strategy Fixed Effects	Yes	Yes	Yes
Years Fixed Effects	Yes	Yes	Yes
R-Squared	0.181	0.475	0.743
N	7,154	8,479	8,563

NOTES: This exhibit reports coefficient estimates from multivariate regressions on global PE fund returns, which are impacted by geographical diversification on the funds' investment returns. The *t*-statistics, derived from robust standard errors clustered by fund, are in parentheses. * significant at the 5% level; ** significant at the 1% level.

a significant t statistic for the quadratic function of country count (country count^2). Referencing Exhibit 3C, we show positive coefficients for Net IRR and TVPI.

We show both positive coefficients and significant results for DPI at the 1 percent significance level (*t* stat = 2.56) for the country count variable. This is reinforced with negative coefficients and significant *t* statistics at the 5 percent significance level for the quadratic function of country count (country count^2) for Net IRR (*t* stat = –2.07) and at the 1 percent significance level for TVPI (*t* stat = –3.82) and DPI (*t* stat = –5.44). Consistent with past studies on industry diversification, the results suggest that some geographical diversification may be initially beneficial for PE fund returns, but when PE funds engage in excessive geographical diversification, PE fund returns will experience an adverse impact after reaching an inflexion point, demonstrating an inverted U-shaped relationship with geographical diversification.

Robustness Checks and Endogeneity Treatments

We include robustness checks by using an instrument variable and 2SLS regression model analysis consistent with best practices from studies done by Ewens and Marx (2017) and Bernstein (2015). The concern with endogeneity issues in finance research relates to other variables that have not been included in the regression model impacting the main effect independent variable, which is the country count variable that proxies for geographical diversification. The instrument variable selected, which is the host country stock market capitalization of the headquarters office of the PE fund, satisfies the exclusion restriction condition, which is required to confirm its suitability as an instrument variable. A comparison of the coefficient estimates, students' *t* statistics and z statistics in OLS regression, first stage and the 2SLS regression analysis is shown in Exhibit 4. The data further reinforce the main finding in our study that there is a negative correlation between geographical diversification and PE fund returns, and the results are significant for TVPI and DPI at the 1 percent level using both OLS and 2SLS regression methods.

Alternative Explanations

We suggest two alternative explanations: (a) PE funds that are geographically diversified are more conservative than single geographic PE funds and hence generate lower returns; (b) PE funds that have more investment staff resources or manpower on the ground will be able to cope with demands of geographical diversification. We address this issue using an additional multivariate regression model that includes the Public Market Equivalent (PME) ratio as a dependent variable. Unlike the dependent variables used in the study, which include the IRR, TVPI, and DPI, the PME ratio as a performance metric uses cash flow distributions from PE funds and compares it with equivalent cash flows from a publicly listed index distributed to investors during the same period. This will incorporate a risk adjustment into the performance evaluation of PE funds that are geographically diversified against PE funds that are

EXHIBIT 4

OLS and 2SLS Multivariate Regression Model Estimates and Model Results

	Dependent Variables Being Studied in the Models					
	OLS Regression Estimates		First Stage		2 SLS Regression Estimates	
Independent Variables	Log (DPI)	Log (TVPI)	Log (DPI)	Log (TVPI)	Log (DPI)	Log (TVPI)
Country Count	–0.029**	–0.004**			–0.086**	–0.020**
	(–2.99)	(–2.94)			(–2.86)	(–2.94)
Log (fund size)	0.031**	–0.001**	0.066**	0.066**	0.032**	0.012**
	(4.24)	(–5.14)	(5.30)	(5.22)	(4.01)	(–6.56)
Fund Age	0.022**	0.027**	–0.078**	–0.075*	0.220**	0.026**
	(10.81)	(7.83)	(–2.73)	(–2.57)	(12.09)	(6.35)
Top Quartile	0.694**	0.300**	0.043	0.039	0.704**	0.302**
	(32.86)	(56.33)	(1.17)	(1.08)	(30.46)	(59.29)
Diverse Industry	0.177**	0.019**	–0.033	–0.034	0.182**	0.016**
	(6.49)	(3.37)	(–0.86)	(–0.88)	(7.44)	(2.93)
Region	0.166**	0.022**	–0.480**	–0.464**	0.133**	0.014
	(4.45)	(2.81)	(–8.98)	(–8.65)	(3.32)	(1.62)
Log(host cappctGDP)			–0.211**	–0.212**		
			(–21.07)	(–21.02)		
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Years Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.742	0.475	0.097	0.097	0.737	0.459
1st Stage F-Stat			17.80	17.54		
N	7,154	8,479	8,000	7,916	8,000	7,916

NOTES: This exhibit reports OLS and 2SLS (2nd stage) coefficient estimates for global PE fund returns, which are impacted by geographical diversification on the funds' investment returns. The *t*-statistics (OLS and first-stage models) and z-statistics (2SLS models) derived from robust standard errors clustered by fund are in parentheses. * significant at the 5% level; ** significant at the 1% level.

not geographically diversified. Due to Preqin having a limited sample of PME data, only 1,600 sample observations are available for analysis, and coverage is for newer vintage PE funds from 2003. We also obtain investment staff numbers but at the parent firm level of the PE funds, which is recently available from Preqin. We develop an interaction variable of invest staff and country count ($invest\ staff \times country_{count}$) to assess whether additional investment staff resources available to PE funds will enable the funds to cope with the adverse effects of geographical diversification.

The multivariate regression model using the PME performance metric is as follows:

$$\begin{aligned} Y_i = constant + X_1(country_{count}) + X_2(\ln fund\ \ size) + X_3(fund\ \ age) \\ + X_4(top\ \ quartile\ \ performance\ \ classification) + X_5(invest\ \ staff) \\ + X_6(diverse\ \ industry) + X_7(invest\ \ staff \times country_{count}) + \varepsilon \end{aligned} \tag{4}$$

where Y_i is the performance return of PE funds using PME to incorporate risk adjustments. Referencing the regression output results in Exhibit 5, the country count variable (country count) is still significant at the 10 percent significance level with a negative coefficient (t stat = –1.90). Hypothesis one (H1) of the study is still supported in this case, taking into consideration the risk adjustment factor provided by the PME performance metric as a dependent variable in the model. This result provides an empirical argument for the alternative explanation that PE funds that are geographically diversified underperform PE funds that are not geographically diversified due to risk aversion and conservatism. In addition, regression results

EXHIBIT 5

Multivariate Regression on the Impact of Geographical Diversification on PE Returns Using the PME Ratio

	Dependent Variable
Independent Variable	**Log (PME)**
Country Count	–0.066
	(–1.900)
Log (fund size)	0.003
	(0.740)
Fund Age	–0.014
	(–1.480)
Top Quartile	0.001
	(0.130)
Invest Staff	–0.003
	(–1.860)
Diverse Industry	0.010
	(0.740)
Invest staff x Country Count	0.020
	(1.800)
Region	0.010
	(0.550)
Strategy Fixed Effects	Yes
Years Fixed Effects	Yes
R-Squared	0.032
N	1576

NOTES: This exhibit reports coefficient estimates from multivariate regressions on global PE fund returns, which are impacted by geographical diversification of the funds' investment returns. t-statistics derived from robust standard errors clustered by fund are in parentheses. * significant at the 5% level; ** significant at the 1% level.

show that the interaction variable of investment staff and geographical diversification (Invest staff x Country count) shows a positive coefficient and is significant at the 10 percent level (t stat = 1.80). This provides an empirical argument that PE funds with access to more investment staff resources on the ground can better cope with the adverse effects of geographical diversification. A future area of research is to tackle an alternative explanation that multi-geographic PE funds generate lower returns than single geographic PE funds due to higher costs of executing transactions in multiple locations when fund operating expense data become available from proprietary databases.

ADDITIONAL FINDINGS

Comparison of Aggregate Performance Benchmarks

We use an alternative PE dataset from Eikon Refinitiv that provides more extensive observations of PE fund returns using the PME ratio compared to Preqin's PME ratio performance dataset. However, the Eikon Refinitiv dataset is presented on an aggregate performance benchmark basis, unlike Preqin, which is based on individual fund data entries. We are thus unable to incorporate regression modeling into the data analysis for the Eikon Refinitiv dataset. We review aggregate performance benchmarks of PE funds investing in single geographic locations and multi-geographic locations in the following locations.

- North American focus PE funds versus Global region PE funds
- Chinese focus PE funds versus Asia Pacific region PE funds
- Australian focus PE funds versus Asia Pacific region PE funds
- Germany and France focus PE funds versus Europe region PE funds

North America is historically the most active PE market and focal area of past PE research. China is the largest PE market in the Asia Pacific by assets under management, deal flow and dry powder. China has 60 percent of Asia's total assets under management and constitutes 21 percent of Asia's PE investment according to Preqin's 2022 alternatives report on private equity and venture capital.[5] Australia has a highly developed PE market in Asia and is a popular investment jurisdiction for private capital due to its safe-haven investment status. France and Germany combined constitute 26.2 percent of the assets under management in Europe, the second largest contribution of all European countries after the UK.[6] Due to BREXIT considerations, we have omitted the UK from a performance comparison with Europe. These reasons provide the impetus for comparing the performance of specific single geographic PE funds against their regional peers.

[5] Preqin Alternatives in 2022 report and webinar on private equity and venture capital.

[6] European Fund and Asset Management Association 2021 report.

EXHIBIT 6

Summary Descriptive Statistics

	Global Region		Asia Pacific Region			Europe Region	
Descriptive Statistic	Global	North America	Asia Pacific	China	Australia	Europe	France and Germany
Mean	1.172	1.278	1.101	1.162	1.121	1.253	1.362
50th Percentile	1.143	1.299	0.948	0.995	1.061	1.151	1.292
75th Percentile	1.532	1.420	1.219	1.355	1.180	1.599	1.847

NOTES: This exhibit shows the descriptive statistics of the aggregate performance of PE funds that invest in a single geographical location (except France and Germany) versus the aggregate performance of PE funds that invest in a region or multiple geographical locations. The combined performance data for France and Germany is a composite benchmark provided by Eikon Refinitiv. PE fund vintages are obtained from 1986 to 2021 and consist of 2,506 funds.

SOURCES: Cambridge Associates, Standard & Poor's.

We include descriptive statistics of the analysis in Exhibit 6. We discern that the aggregate performance of North American PE funds outperforms the aggregate performance of global PE funds. North American PE funds have a mean PME ratio of 1.278 versus global PE funds with a mean PME ratio of 1.172. The descriptive statistics also show that North American funds have a superior 50th percentile PME ratio of 1.299 versus global PE funds, which show a 50th percentile PME ratio of 1.143. From the Asia Pacific standpoint, PE funds investing in a single geographical location of China outperform the cross regional Asia Pacific funds on an aggregate performance benchmark basis using the mean, 50th and 75th percentile PME ratio. We assess the performance of single geographic PE funds investing solely in Australia to be superior to that of Asia Pacific PE funds on an aggregate benchmark basis from the mean and 50th percentile PME ratio. For Europe, we find that PE funds in France and Germany combined based on a composite performance benchmark by Eikon Refinitiv outperform the aggregate performance benchmark of Europe regional funds in the mean, 50th, and 75th percentiles. This analysis using a larger Eikon Refinitiv dataset supports the study findings using regression modeling and the Preqin dataset.

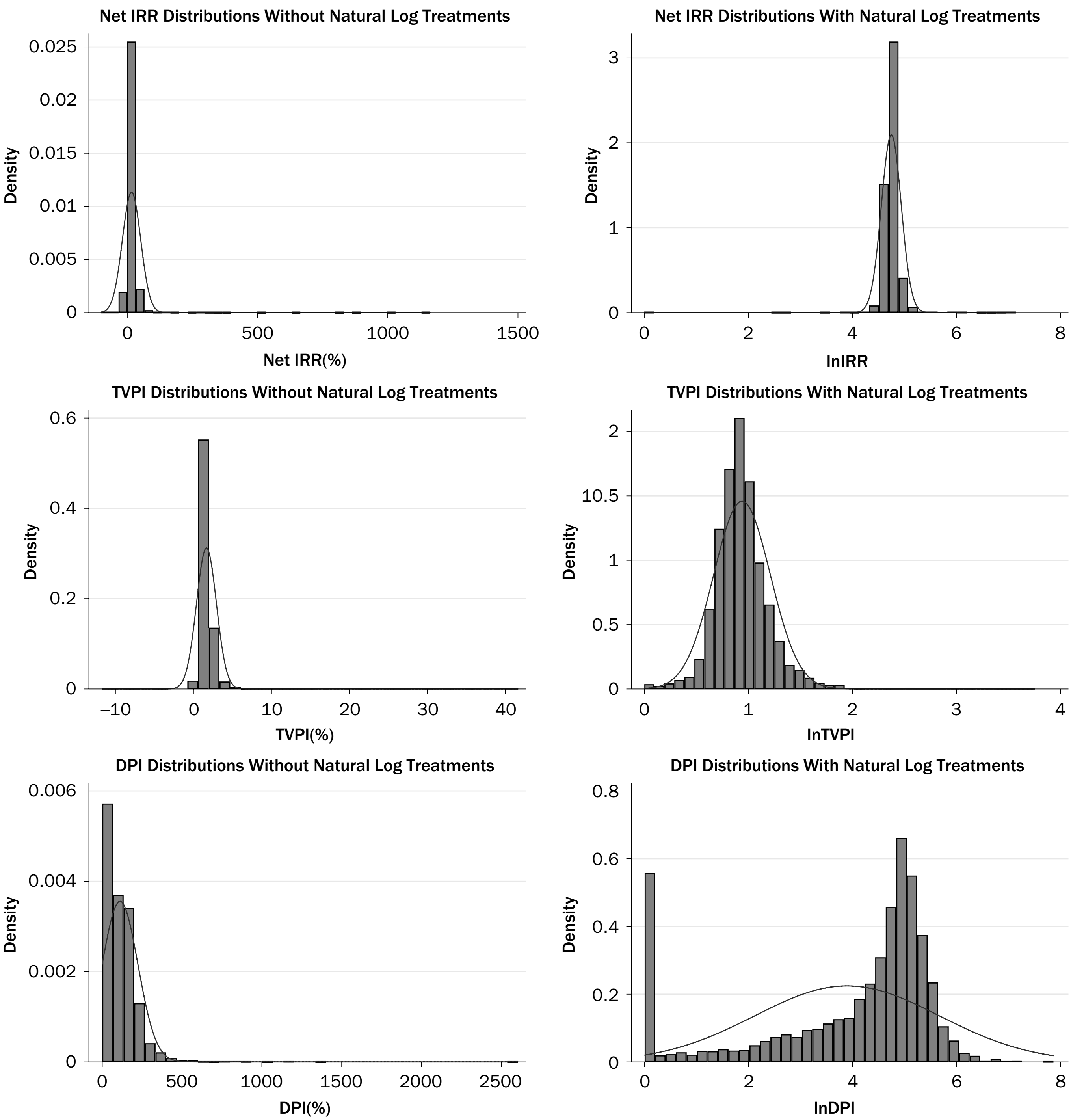
CONCLUSION

We analyze the impact of geographical diversification on the returns of global PE funds, an area of PE research that has not been given due attention in past studies. Our findings show that there is a negative correlation between geographical diversification and PE fund returns. The main regression model indicates significant results for all 3 dependent variables used to proxy for PE fund returns and for the main effect variable which proxies for geographical diversification in PE funds. Findings in the main regression model also show that a one standard deviation increase in geographical diversification is associated with an 18.8 percent reduction in PE fund returns from a Net IRR perspective. The reduction in PE fund returns is 3.72 percent from a money multiple or TVPI perspective given a similar change in geographical diversification.

We find that fund age and industry diversification in PE funds mitigate the negative correlation between geographical diversification and PE fund returns. The relationship between geographical diversification and PE fund returns follows an inverted U-shaped relationship where PE funds that have excessive geographical diversification experience an adverse impact on returns after reaching an inflexion point. We reinforce our main findings using endogeneity treatments.

Empirical analysis using the Public Market Equivalent (PME) supports the main study findings and addresses the alternative explanation that multi-geographic PE funds underperform due to risk aversion and conservatism. PE funds with additional investment staff resources on the ground can cope with the adverse effects of geographical diversification. Analysis of a larger dataset using the PME metric by an alternative data provider also suggests superior performance of single geographic PE funds versus Asia Pacific, Global, and Europe regional PE funds on an aggregated performance basis. A future area of research is to obtain fund operating expense data when it becomes available to address another alternative explanation that PE funds investing in multi-geographic locations generate lower returns due to higher cost structures.

APPENDIX



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