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

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I hereby declare that this Doctor of Business Administration dissertation is my original work

and it has been written by me in its entirety.

I have duly acknowledged all the sources of information

which have been used in this dissertation.

This Doctor of Business Administration dissertation has also not been submitted for any degree

in any university previously.

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Victor Ong Hock Keong

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Abstract

Impact of geographical diversification and limited attention

on private equity fund returns

By Victor Ong Hock Keong

This study analyzes the effect of geographical diversification on global private equity (PE) fund returns. I 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, I employ an instrument variable analysis where the instrument used is the stock market capitalization value of the host country where the PE fund is based. My results apply to Net IRR, multiple 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 a 18.8 percent reduction in PE fund returns from a Net IRR perspective in the main regression model. Fund age and industry diversification helps mitigate the negative correlation between geographical diversification and returns. Evidence indicates that the relationship between geographical diversification and PE fund returns follows an inverted U shape function. Endogeneity treatments further validates the instruments in the model and reinforces study findings.

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Chapter 1 Introduction

Private equity (PE) has funded the expansion of family owned small and medium enterprises (SMEs), technology start-up companies, infrastructure projects, real estate assets and large publicly listed companies. Preqin, a global data service provider for alternative investments indicates that global PE assets under management has hit USD 4.11 trillion as of June 2019 with USD 595 billion of PE funds closed in 2019 alone. Assets under management (AUM) by PE funds is expected to reach USD 4.7 trillion by 2023[1]

PE funds are investment vehicles managed by professionals known as General Partners (GPs) who deploy capital from investors into predominantly private market assets. Investors of PE funds, the Limited Partners (LPs) are typically pension funds, endowments, insurance companies, financial institutions, sovereign wealth funds (SWFs) and family offices. The contractual relationship between GPs and LPs is govern by a legal agreement known as the Limited Partnership Agreement (LPA). GPs of PE funds are compensated through a fixed management fee and carried interest structure. A typical PE investment structure is the 2 and 20 model where GPs receive a 2 percent annual management fee a 20 percent carried interest for performance.

PE has its historical roots in North America but its growth has been rapid as an alternative asset class in the Asia Pacific region. Despite its growing importance both globally and in the Asia Pacific region, scant research has been done in this area with most of the past studies focussing on the North American PE market. There is a gap in PE research especially in specific themes and niche areas which presents an opportunity for further research. The established theories in finance advocate for either concentration or for financial diversification. In traditional portfolio theory, due to the benefits of portfolio diversification in risk reduction, a portfolio manager will hold a basket of diversified assets in a portfolio 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. Investors are not rewarded for holding investments with non-diversifiable or idiosyncratic risk which should be diversified away. Ross (1976) further added refinements to the work on the CAPM model through the introduction of the arbitrage pricing theory (APT) model which advocates for fully diversified investor portfolios except for systematic or non-diversifiable risks in investor portfolios.

[1] 2020 Preqin global private equity and venture capital report Pg 15-16

Established finance theory thus assumes investors to have fully diversified 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. Through the inclusion of more assets, a fully diversified portfolio will dominate all other portfolios which are less diversified. However, in PE investments, concentration or focus is essential to implement value creation initiatives that enable PE funds to obtain higher portfolio valuations, undertake successful deal exits and achieve targeted returns. Industry studies show that PE fund returns are impacted more by how PE portfolio firms are being managed rather than through market conditions or deal structuring. A joint study by London Business School, New York University and McKinsey[2] proposes that additional returns generated by PE funds are due to strategic, operational and governance improvements rather than financial engineering where leverage drives returns.

PE funds that tend to overstretch their resources and capabilities by investing in multiple geographical locations may suffer from a limited attention issue that can adversely impact PE fund returns. However, there are also benefits in having a diversified portfolio of PE investments as economic cycles and macroeconomic conditions impact countries at different stages. An argument can be made for global PE funds to also invest in multiple geographic locations consistent with the diversification argument. I will explore if geographical diversification has a negative correlation with PE fund returns and impose a diversification discount on PE fund returns. This is an aspect of PE research which has not been explored in previous studies before in sufficient depth. Furthermore, the dilemma faced by PE funds on whether to embark on geographical diversification or adopt a concentration or focus approach has been a topic of robust debate amongst GPs and LPs during industry conferences. GPs as part of their overall fund conceptualization strategy will need to make crucial decisions on whether they should focus on just a single geographic fund or adopt a multi geographic approach during fund-raising efforts. The decisions undertaken by GPs on this issue will also impact staff recruitment as identifying PE professionals with specific or diverse geographical expertise will be critical in supporting the eventual investment strategy. Discussions with GPs and LPs reveal that this subject remains a key area of interest in the industry. However, a credible study which provides the industry with tangible conclusions on this topic remains

[2] Private Equity vs PLC Boards in the UK: A comparison of practices and effectiveness, Journal of Corporate Finance Volume 21 Number 1

elusive. GPs are interested to learn whether findings using robust methodology is consistent with their own experiences in the industry.

The study will investigate the question of whether geographical diversification by PE funds will have an impact on PE fund returns. GPs investing in multi geographical locations may suffer from limited attention issues in comparison to investing in a single location using a concentration approach which may be less impacted by limited attention issues. The study will establish if certain attributes of PE funds, which can include fund age and industry diversification of the PE funds will mitigate or weaken the impact of geographical diversification on PE fund returns. I will investigate if the relationship between geographical diversification and PE fund returns follows an inverted U shape function where excessive geographical diversification has a negative effect on PE fund returns after an inflexion point.

The main findings highlight that PE funds pursuing extensive geographical diversification generate lower returns compared to PE funds investing in single geographic location which can be link to limited attention issues consistent with past studies on hedge funds, mutual funds and publicly listed markets. A multivariate ordinary least squares (OLS) regression model which includes interaction variables and controls known as the main regression model show significant results pervasive in all 3 dependent variables used to proxy for PE fund returns. Findings show that a one standard deviation increase in geographical diversification proxied by a country count variable will result in an 18.8 percent reduction in PE fund returns from a Net IRR perspective in the main model. The relationship between geographical diversification and PE fund returns follows an inverted U shape function when a quadratic function of the geographical diversification variable is included in the model.

The paper is organized in several sections beginning with a literature review in the next chapter on past PE studies, highlight proposed research hypotheses and model development, explain the data and methodology adopted and discuss empirical results of the study. Several alternative explanations will be address in the discussion section and the paper will conclude with possible future areas of research.

Chapter 2 Literature Review

The bulk of PE research has focus on performance measurement but from a North American centric perspective. Harris, Jenkinson and Kaplan (2014) find that PE buyout funds on average outperform the S&P500 index by 27 percent over the fund's investment horizon, an outperformance of 3 percent annually. Jegadeesh, Kraussl and Pollet (2015) study the performance of fund of fund investments into unlisted PE funds and show PE funds generate annual returns of between negative 0.5 percent and 2 percent. Acharya, Gottschalg, Han and Kehoe (2013) find positive abnormal performance after analyzing PE transactions and controlling for leverage and sector effects. Cochrane (2005) find VC funds achieving a mean return of 15 percent after adjustments. Robinson and Sensoy (2013) find no evidence that PE funds with higher fixed fees underperform net of fees compared to lower fixed fee funds.

Phalippou and Gottschalg (2009) criticizes PE performance, finding on average a net of fees performance of 3 percent below the S&P 500 index and 6 percent below the same index after risk adjustments. Phalippou (2020) finds PE returns of 11 percent in comparison to small capitalization public indices since 2006 which is not stellar.

Kaplan and Schoar (2005) in the seminal paper posit that buyout PE funds and venture capital (VC) funds have on average outperform the S&P 500 returns on a gross of fees basis. GPs whose funds outperform the industry in one fund vintage are likely to outperform the industry in the next vintage fund demonstrating performance persistence.

Performance persistence is a topic of considerable interest as this provides credence on the sustainability of PE returns. Braun, Jenkinson and Stoff (2014) find performance persistence in both top quartile and bottom quartile PE funds using deal cash flows. However, performance persistence of the top quartile funds declines as PE markets mature and with competition intensifying in the industry. Performance persistence of the bottom quartile PE funds remain unchanged regardless of competitive intensity and generating anaemic returns.

Korteweg and Sorensen (2017) find significant long-term persistence in returns and a performance differential between top and bottom quartile PE firms net of fees by around 7 percent to 8 percent per annum. Identifying PE funds that will achieve top quartile performance is challenging as the track record of top quartile PE funds has been inconsistent. Cavagnaro, Sensoy, Wang and Weisbach (2019) posit that skill and expertise of an LP are critical drivers of LPs' returns when investing in PE funds. Hochberg, Ljungqvist and Jorgensen (2013) acknowledges the presence of skill in the performance persistence of VC funds. VC performance persistence is also attributed to information asymmetry between existing and new investors during fund assessments by new investors.

Several other factors impact PE performance persistence. Sensoy, Wang and Weisbach (2014) find that the superior performance of endowment investors in the 1991 to 1998 period is due to greater access to top performing VC funds while in the latter period of 1999 to 2006, these endowment investors generate inferior performance when access to top performing VC funds is no longer evident. Bucher, Mohamed and Schwienbacher (2016) find that risk is an important driver of performance persistence in PE funds. Ewens, Michael, Jones and Rhodes-Kropf (2013) show diversifiable risk should be priced in VC deals even in fully diversified investor portfolios. Harris, Jenkinson and Stucke (2012) mention difficulties of classifying PE funds as top quartile due to a lack of PE performance benchmarks.

Regarding PE fund raising, Barber and Yasuda (2017) find that GPs are more likely to raise a larger successor fund after experiencing a credible performance in the interim period. GPs tend to time their capital raising programs opportunistically during successful deal exits. GPs with less stellar reputations appear to window dress performance during fundraising periods by managing transaction valuations during deal exits. Less reputable PE funds revalue portfolio investments downwards in the post fund raising period.

Investor capital is committed for up to 10 years and PE is an illiquid investment which requires a liquidity premium. Robinson and Sensoy (2016) find that variations in PE funds' cash flows can be diversified away and link to fund specific properties or to its vintage year. Franzoni, Nowak and Phalippou (2012) argue that PE also suffers from the same liquidity risk factors as public equity markets and other alternative assets. Liquidity risk premium for PE is about 3 percent on an annual basis which translates into a 10 percent discount factor for valuing PE investments. This negates prior superior performance of PE funds in comparison to public market indices. Nadauld, Sensoy, Vorkink and Weisbach (2018) find transaction costs in secondary PE investments are large and impact funds operating between 4 to 9 years from vintage years and are attributed to information asymmetry between PE and portfolio firms.

On PE investment mandates, De-Silanes, Phalippou and Gottschalg (2015) suggest that PE firms that have an investment mandate based on portfolio growth using a repetitive deal accumulation strategy will experience suboptimal returns. PE firms that focus on making few but concentrated investments and have access to unique investment teams can produce superior returns. On the topic of PE investment strategy, Fang, Ivashina and Lerner (2014) find co-investments as an investing strategy underperform in comparison to direct PE investments. This is due to LPs only being able to access inferior residual opportunities after GPs have prior access to superior opportunities. Braun Jenkinson and Schemmerl (2019) find no evidence of co-investment strategy having an adverse impact on PE returns.

An increasing number of LPs are also sovereign wealth funds (SWFs) that manage PE portfolios. Dewenter, Han and Malatesta (2010) find significant positive or negative returns associated with these transactions coinciding with SWF announcements of investments or divestments. SWFs take active and influential roles as PE investors. In contrast, Kotter and Lel (2011) find SWFs to be passive investors that prefer to invest in sizable and underperforming companies in financial distress. Bortolotti, Fotak and Megginson (2015) find evidence of a statistically and economically significant "SWF discount" in which SWF stock purchases exhibit a smaller valuation impact on target firms compared to stock purchases by private investors. Sethi (2018) mention PE funds acquired by SWFs can be influenced by SWF objectives.

Besides performance measurement, performance persistence, liquidity issues, investment mandates, strategies and SWF issues, three important factors which require discussion before the focal area of PE diversification involves PE fund size, limited attention issue and fund age.

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 or the capacity constraint issue by industry practitioners. Humphery-Jenner (2011) 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. Smaller PE funds due to cost structures are less prone to agency issues compared to the larger PE funds. Larger PE funds have fewer staff per investment and are not well positioned to offer management expertise essential for value creation in early-stage start-ups and seed companies. Smaller PE funds are better suited for value creation activities in portfolio firms due to structural advantages that comes with being a smaller fund.

Marquez, Nanda and Yavuz (2014) find that GPs keep fund sizes small due to the effort needed to attract superior performing entrepreneurs to accept PE investment. These efforts impose a constraint on fund size. Fulghieri and Sevilir (2009) find that VC firms with large number of high potential portfolio companies keep portfolios smaller to focus on value creation activities. VC firms enlarge portfolio sizes when there is a reduction in the quality of portfolio companies. Kanniainen and Keuschnigg (2003) argues that the optimal size of VC portfolios can be link to the amount of advice that VCs can provide to portfolio companies. Cummings (2006) find VC fund size being impacted by several factors, firstly related to the types of VC funds where corporate VC funds and privately owned independent VC funds have smaller portfolios compared to government affiliated funds. Secondly, VC funds that engage in frequent fundraising efforts and have more investment managers have larger portfolios. VC firms which consist of two or more funds have smaller portfolios. VC funds investing in the life sciences sector have larger portfolios while VC funds that focus on sectors outside of life sciences but within the high-tech sector and are present in several geographical locations have smaller portfolios. VC funds that invests during periods of booming stock market returns have larger portfolios compared to funds that invest during periods of stock market normalcy. Bernile, Cumming and Lyandres (2007) opine that the optimal size of VC fund portfolios involves a cost benefit analysis of the ex-ante value of a portfolio investment versus portfolio monitoring effort. Cumming and Dai (2010) find a convex relationship between VC fund size and the valuation of the portfolio companies. Larger funds may have superior bargaining position but is impacted by limited attention. The limited attention issue increases pre-money valuation of firms which impact PE returns and affects less experienced funds.

The limited attention issue has also been observed in past studies of hedge fund performance. Lu, Ray and Teo (2015) show that both marriage and divorce are associated with deterioration of risk adjusted hedge fund performance. Hedge fund performance alpha falls by 8.50 percent per annum in the six months period surrounding marriage and 7.39 percent per annum in the same window surrounding a divorce. The authors also find that the impact of marriage and divorce is most poignant for busy fund managers in charge of numerous funds or who are not part of a team. Corwin and Coughenour (2008) allude to limited attention issues that liquidity traders in publicly listed stock markets face where these traders focus more on actively traded stocks compared to thinly traded stocks as they monitor a larger portfolio of stocks. Peng and Xiong (2006) mention investors tend to focus on market and sector specific information rather than company specific information when they are dealing with limited attention issues and this scenario in combination with investor overconfidence can result in asset price movements which are not explain by rational expectation models. Mukherjee and Pareek (2020) mention limited attention having impacting mutual fund managers' ability to efficiently allocate their task focus when taking asset positions requiring information acquisition efforts. Zhang and Wang (2015) observe investors' limited attention impacting performance in the ChiNext market in China. These findings provide an angle to explore the impact of limited attention on PE funds pursuing geographical diversification.

Past academic studies on the relationship between PE performance and fund age or experience has not been as extensive in comparison to studies on PE performance and fund size. Younger and newly established PE funds are willing to take on additional risks for reputation enhancement in the industry. Gompers (1996) in the seminal contribution to this topic argues that new and younger PE funds have a higher propensity to take on risk at the initial stages of a fund's life for brand and reputation development. Gompers (1996) further reiterates that younger VC funds take their portfolio companies public earlier in comparison to other established funds for reputation development in the industry. Portfolio companies of newer VC funds are younger and have higher levels of IPO under-pricing compared to the more established VC funds. Gompers, Kovner, Lerner and Scharfstein (2008) posit that the more experienced funds have an advantage in their ability to make superior investment decisions when public market conditions are changing without impacting performance. Giot, Hege and Schwienbacher find that new and inexperienced funds tend to invest more slowly than experienced funds but the size and magnitude of the investments in terms of absolute value and as a proportion of total fund size is larger for the younger funds. The observation of increasing investment sizes over time becomes prominent after the fund has a successful maiden exit and is evident in VC funds but not in buyout funds. Younger funds have relative underperformance to their more established peers and this performance shortfall is particularly significant for the more sizable investments. Ljungqvist, Richardson and Wolfenzon (2019) find that the older and experienced funds can increase the pace of investments whenever market conditions improve. Maiden first time funds do not exhibit the same market awareness as more experienced funds. Younger funds prefer riskier buyout deals. First time funds limit risk exposures after superior performance.

Kandel, Leshchinskii and Yuklea (2011) discuss fund aging and its impact on performance through models that allude to an agency problem between LPs and GPs due to the finite investment horizon of a VC fund. The information asymmetry between GPs and LPs can be a factor leading to GPs' suboptimal investment decisions where GPs continue funding inferior projects and divest these projects to buyers as incomplete but credible projects as long as buyers lack the capabilities to evaluate these projects. GPs in the absence of proper compensation may also not keep abreast of good projects but delay prone projects which impedes fund performance as its investment horizon gets progressively reduced. There is also evidence of the disconnect between GP and LP incentives by observing NASDAQ market corrections in the post 2000 period where average number of abandoned projects is almost twice the rate compared to earlier periods prior to the NASDAQ correction. Post NASDAQ correction period, older VC funds are significantly more predisposed to abandoning good projects compared to the younger VC funds. Corporate VC funds do not exhibit these effects due to being exempt from the limitations of having a fixed investment time horizon. This effect has been associated with significant levels of information asymmetry in high tech firms.

Past studies on the relationship between geographical diversification and its impact on PE returns has been inconclusive and forms the main focal point of the literature review and this study. Humphery-Jenner (2013) analyze a sample of 1,505 PE funds with vintage years from 1980 to 2007 to assess the impact of diversification on PE returns. The multivariate regression model in the study has control variables for fund sizes, transaction sizes and number of investment funding rounds. The study results indicate PE returns improving with diversification. The positive correlation between diversification and PE returns has been link to the benefits of information sharing. Findings also suggest that industry diversification in previous vintage funds elevate IRR performance in subsequent funds due to knowledge accumulation and transfer within firms. The study did not show any conclusive findings on the effect of geographical diversification on PE returns but find that regional diversification has a positive impact on the performance of seed funds as seen from higher IRRs. Extensive industry diversification which stretches staff resources and induces limited attention issues can attenuate PE returns. Observations of a reduction of PE returns becomes apparent when diversification efforts are driven by risk aversion rather than management fees. Alternative explanations for the positive effects of diversification on PE returns is link to diversification being able to reduce firm specific risks and facilitate the efforts of PE funds to pursue higher risk investments. Well diversified PE funds may also have a more stringent selection criteria and avoid low risk and low return prospects where internal knowledge is lacking. There is thus a need to incorporate risk when assessing the impact of geographical diversification.

Lossen (2006) find that returns of PE funds decrease across financing rounds but returns increases across different industries. A key point is that the study is unable to find any 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 only UK firms find that firms backed by PE that have specialization by industry and funding stage outperform a peer group without specialization. Huss and Steger (2020) studying PE buyout funds find that diversification within industries helps PE returns while diversification across industries do not. They did not find any significant effects when studying the impact of geographical diversification on buyout returns. The study however has limitations on using a sample of less than 200 PE funds obtain from the holdings of just Swiss pension funds. Bowden, Harjoto, Paglia and Tribbitt (2016) analyzing a sample of US PE funds find both industry or sector diversification and geographical diversification to have positive impact on PE returns especially during periods of strong economic performance. Thus far, past studies conducted by Lossen (2006), Humphery-Jenner (2013), Bowden Et al. (2016) and Huss and Steger (2020) did not explore the involvement of other variables that may help mitigate the effects of geographical diversification on PE fund returns. This may be due to a lack of evidence of the effects of geographical diversification on PE fund returns where limited sample size and geographical coverage can be a factor for the inconclusive results.

In the VC area on diversification, some studies allude to the benefits of specialization on 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. Generalist VC firms that do not specialize have inferior capital allocation abilities in investments across different industries and within a specific industry in comparison to specialist VC firms. Bygrave (1987) argues that VC firms should aim to build specialization capabilities with rapid changes in technology. Only larger VC firms can afford to adopt a multifaceted investment approach while smaller VC firms will have to pivot towards a more focussed investment strategy. Entrepreneurs looking for VC funding should target the firms that specializes in their own technology domain. Gupta and Sapienza (1992) mention VC funds in early stage ventures have less industry and geographical diversification with corporate VC funds having less industry diversification but more geographical coverage. Norton and Tenenbaum (1993) show benefits of information sharing to support a specialization strategy. VCs utilize specialization to control investment risks, enhance reputation and gain access to networks.

Knill (2009) show that neither a concentration approach involving significant VC involvement with the portfolio companies or a strategy pursuing extensive diversification at the portfolio company level will lead to an acceleration of VC firms' growth or more investment exits. Increasing international diversification has a positive impact on VC firm growth. However, the dependent variable used in the study relates to VC firm growth which is not an established performance metric in PE like the Net IRR, multiple or DPI. Cressy, Malipiero and Munari (2012) cite the traditional resource base theory supporting the benefits of VC funds adopting a concentration approach as compared to the alternative theory of financial diversification. The authors study a sample of 649 VC funds from the United Kingdom from 1981 to 2000 and their findings contrast slightly to that of Humphery-Jenner (2013). Geographical diversification by country has positive implications on the success of VC funds while excessive industry diversification has an adverse impact on success. Later stage VC funds are more diversified from a geographical standpoint than early stage VC funds while both late stage and early stage VC funds have similar dimensions of industry diversification. The study uses Net IRR as its dependent variable in contrast to the VC firm growth variable by Knill (2009). Bucher, Mohamed and Schwienbacher (2017) allude that diversified VC funds due to an already lower risk profile pursue higher risk deals hence generating higher expected returns. Matusik and Fitza (2012) opines that VC firms benefit from either high or low levels of diversification because of processing efficiencies or diverse information sources that enable complex problem solving. Moderate levels of diversification provide the most inferior results.

On the topic of VC investments and geography, Cumming and Dai (2010) acknowledge the preference of VC firms to make investments in the proximity of their home locations as having a "local bias". More than 50 percent of new VC investments are located within 233 miles of their VC firms. Older, more established VC firms with better networking capabilities exhibit less "local bias" compared to newer VC firms. VCs that are deal leads or sole investors in a transaction prefer ventures in their local vicinity. Hochberg and Rauh (2013) study pension fund allocations into in state PE fund investments and out of state PE investments and conclude that information edge from investing into in state investments is negated by other adverse factors like mismanagement, inferior managerial talent and political pressures.

Nahata, Hazarika and Tandon (2014) studying PE and geography linkages find that differences in legal mechanisms, legal enforcement, stock market development and cultural differences in countries where VC funds operate in will have an impact on its performance and success. Nahata, Hazarika and Tandon (2014) posit that legal rights protection and stock market development are key drivers for success in VC investments. VC firms that invest in countries with significant culture differences from the VC firms also experience a higher rate of success. Salehizadeh (2005) find that VC investment activity in emerging markets can be explained by variables like GDP per capita, capital inflows and stock market listings. Black and Gilson (1998) consider macroeconomic and stock market indicators to explain VC activity.

Teo (2012) find that nearby PE funds which relate to funds that have headquarters or branch offices located in the investment region have superior performance to distant PE funds which are specifically PE funds that do not have offices in the investment region. Similar outperformance of nearby PE funds compared to distant PE funds is also evident after controlling for fund size differences. Nearby PE funds have smaller fund sizes compared to distant PE funds with distant PE funds having superior capital raising capabilities.

Studies of geographical diversification and PE are also link to corporate governance issues and how legal systems can impact PE returns. Lerner and Schoar (2005) find that transactions in countries with stricter legal enforcement provide higher returns and valuations. Fleming, Johan and Takeuchi (2011) posit that PE funds can attenuate the negative effects of corruption in countries they operate in and achieve higher returns even after controlling for different legal systems in countries. Cumming and Zambelli (2012) find during periods where leveraged buyouts (LBO) are illegal, LBO deals experience 15 to 20 percent lower returns.

The literature review concludes with a discussion on the endogeneity problem in finance research. The endogeneity problem manifests itself when a main effect independent variable which is intended to explain variations in the dependent variable of a regression model is impacted by other variables which has not been included in the regression model as exogenous variables. In PE research, this issue can determine whether the value creation experienced by the PE fund's portfolio company can be attributed to either the fund's screening or selection of superior portfolio companies is due to the fund's monitoring activities. Typical monitoring activities include improving a portfolio company's corporate governance, appointing high quality C-suite executives and opening doors to new customer contacts. Hellman and Puri (2002) find VC firms make changes at the C suit level as well as implementing policy directives which results in a higher level of professionalism in firms. These activities are beyond the scope of financial intermediaries. Kaplan and Stromberg (2001) mention the selection, contracting and monitoring activities of VC funds minimizing the principal and agency conflict between VC investors and portfolio companies. Engel and Keilbach (2007) find no difference in innovation activity of German firms through patents granted before and after receiving venture funding.

Bernstein, Giroud and Townsend (2016) differentiate the selection and monitoring effects of VC funds on their portfolio companies through the inclusion of a shock variable in the form of an introduction of direct airline fights which reduces the travelling time of VCs to their existing portfolio companies. An extensive survey of VC funds indicates VC involvement in portfolio firms increasing with the introduction of direct flights and reduced travelling time.

Ewens and Marx (2018) show founder replacement in start-ups leads to an improvement in performance by using an instrument variable in the form of changes to 14 US state constituencies' non-compete laws from 1995 to 2016. Non-compete laws constrain free flow of human capital and makes it difficult to hire replacements for start-up founders. Using this instrument variable and 2 SLS regression model, results reverse initial findings of the study.

Chemmanur, Krishnan and Nandy (2011) assess the performance of VC backed portfolio companies compared to non-VC backed portfolio companies before and after the portfolio companies received VC financing. The authors use a matching sample analysis in combination with a propensity scoring technique similar to Chemmanur, Loutskina and Tian (2014).

Studies conducted by Humphery-Jenner (2013), Lossen (2006) and recently Bowden et al. (2016) and Huss and Steger (2020) provide minimal description of endogeneity treatments in study findings. This is a gap in studies which I will address through endogeneity treatments.

Chapter 3 Research Hypotheses and model development

The literature review shows that there is a gap in past research on the relationship between geographical diversification and its impact on PE returns. Recent research in PE studying the effects of diversification undertaken by Lossen (2006), Knill (2009), Humphery-Jenner (2013), Cressy, Malipiero and Munari (2012) and most recently Bowden Et al. (2016) and Huss and Steger (2020) did not address this research question in sufficient depth given the limited geographical coverage and sample size of the PE funds in these studies. Studies have instead focus on the effect of industry diversification on PE returns with geographical diversification having a secondary role due to the North American centric focus of these studies. Findings from these studies show that industry diversification by PE funds result in higher PE fund returns due to the internal knowledge accumulation and transfer of this knowledge. PE funds should however be wary of stretching their resource capabilities as they can be susceptible to limited attention issues which may have adverse consequences on PE returns. Past studies indicate the adverse effects that limited attention can have on hedge funds, listed public equities and mutual funds. However, recent research on the impact of limited attention on PE funds as they pursue geographical diversification has either been lacking in depth or show inconclusive findings. This provides an opportunity to investigate the impact of limited attention on returns especially in the case of PE funds pursuing geographical diversification.

The literature review reveals PE fund attributes like reputation, experience and industry expertise can have a positive effect on returns and which may help PE funds cope with limited attention issues associated with excessive geographical diversification. Past studies show that more experienced VC funds outperform less experienced funds and can make effective decisions whenever market conditions change. I will observe how PE experience as proxied by fund age can moderate the effects of geographical diversification on PE fund returns.

There have been observations from Cummings and Dai (2010) that limited attention experienced by larger funds which results in overpayment for deals impacts less experienced VC funds more seriously. Studies by Humphery Jenner (2013) and Lossen (2006) also find that industry diversification by PE and VC funds can have a positive impact on returns and industry expertise is an attribute valued by GPs in staff recruitment. Huss and Steger (2020) find diversification within industries helps buyout performance and mentions the positive impact of industry diversification on PE returns. The authors allude to the advantage of superior industry expertise on the ability to make good investment decisions. In addition, Bowden, Harjoto, Paglia and Tribbitt (2016) posit that both sector or industry diversification and geographical diversification can have positive impacts on PE returns especially during strong economic cycles. 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 also makes intuitive sense 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 diverse industry expertise. Cambridge Associates in a 2014 study find that PE funds with deep industry or sector expertise in consumer, financial services, health care and technology generate superior returns compared to other peer comparison groups[3]. Bain (2021) mentions in a 2021 private equity report[4] 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.

Humphery Jenner (2013) refer 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 impact on PE returns after an inflexion point. I will evaluate if an inverted U shape relationship also exist for geographical diversification and PE fund returns by using a quadratic or square function for

[3] Declaring a major: sector-focused private investment funds: Cambridge associates research September 2014
[4] Bain 2021 Global private equity report Pg 8
https://www.bain.com/globalassets/noindex/2021/bain_report_2021-global-private-equity-report.pdf

the geographical diversification variable in the study and evaluating the results from this regression analysis. After reviewing the existing PE literature, I propose the following hypotheses for the study:

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.

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

The baseline regression model is as follows:

Yi = constant + X_1 (ctry_count) + X_2 (natural log of fund size) + X_3 (fund age) + X_4 (top quartile performance classification) + X_5 (diverse industry) + Ɛ

Where X_1 (ctry_count) is the main effect independent variable that will proxy for the effect of geographical diversification in PE funds, X_2, X_3 and X_4 are the independent and control variables for fund size, fund age and top quartile PE performance. X_5 is a control variable in the form of a dummy variable to identify whether PE funds have diversified industry investments or are focus on only specific industries like information technology or semiconductors.

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

Yi = constant + X_1 (ctry_count) + X_2 (natural log of fund size) + X_3 (fund age) + X_4 (top quartile performance classification) + X_5 (diverse industry) + X_6 (fund age x ctry_count) + X_7 (diverse industry x ctry_count) + Ɛ

Where Yi is the performance return of PE funds proxied by the dependent variable of Net IRR, multiple (TVPI: Total value over paid in) and DPI (Distributions over paid in)

Where X_1 (ctry_count) is the main effect independent variable that will proxy for the effect of geographical diversification in PE funds, X_2, X_3 and X_4 are the independent and control variables for fund size, fund age and top quartile PE performance. X_5 is a control variable which has been developed as a dummy variable to identify PE funds having diversified industry investments or are focussing on only specific industries like the semi-conductor industry or information technology.

X_6 is the variable for the interaction effect of fund age and geographical diversification (ctry-count) and X_7 is the variable for the interaction effect of industry diversification (diverse industry) and geographical diversification (ctry_count) in PE funds.

A natural logarithm treatment is applied for the variable X_2 (natural log of fund size) after reviewing the normal distribution of the variable using histogram chart analysis available in STATA. Figure 1 in the appendix section illustrates the histogram chart analysis of the fund size variable data and after reviewing the data distribution, the study will implement a natural log treatment for the fund size variable X_2.

[Insert Figure 1 here]

For the independent variable X_3 which is fund age, the study will not be applying the natural log treatment due to scale limitations issue for fund age as the number of years do not exceed 50 years unlike fund size where the scale limits are much larger.

I also implement the same analysis to determine if the dependent variables which are the PE performance metrics will require a similar natural log treatment. Figure 2 shows the histogram chart analysis of the Net IRR variable and I determine that a natural log treatment is not required given the histogram profile analysis. After studying the histogram chart profiles of multiple (TVPI) and DPI (distributions over paid in) in Figures 3 and 4 in the appendix, I will apply natural log treatments to these dependent variables as the variables with log treatments show a better bell curve normal distribution after the treatments.

[Insert Figures 2 to 4 here]

To study hypothesis four (H4), I will utilize the baseline regression model which will include a quadratic function of the main effect geographical diversification variable (ctry_count) which will be classified as ctry_count2 in the regression model.

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

Yi = constant + X_1 (ctry_count) + X_2 (ctry_count2) + X_3 (lnfundsize) + X_4 (fund age) + X_5 (top quartile performance classification) + X_6 (diverse industry) + Ɛ

A separate OLS multivariate regression analysis will be done to reinforce support for hypothesis four (H4). To support the proposed hypothesis that the relationship between geographical diversification and PE fund returns follow an inverted U shape function, the analysis will ideally have to show a positive coefficients and significant students t statistics for the ctry_count variable and a negative coefficient as well as significant t statistics for the quadratic function which is the ctry_count2 variable. I include controls for regions effect, strategy fixed effects and vintage years fixed effects for all the regression models.

Chapter 4 Data and Methodology

I will use secondary data from Preqin's global PE database for the study. Preqin is a database vendor specializing in the collection, analysis and dissemination of alternative investments data which includes PE funds, real estate funds, infrastructure funds, hedge funds and commodities. Additional data which may include stock market capitalization data, stock market returns data, PE industry data or other macroeconomic data will be obtained from other data service providers which can include Bloomberg, Pitchbook, Standard and Poor Capital IQ, Eikon, Thomson Reuters and World Bank macroeconomic databases.

A critical aspect of data collection is to ensure that that there are adequate observations in the sample set, especially for the dependent variables like Net IRR, multiple and DPI. After analysing the data collected from Preqin's PE funds database, I will have 7,154 sample observations for Net IRR, 8,479 sample observations for multiple (TVPI) and 8,563 observations for DPI to be use for the OLS multivariate regression model. In comparison to past PE studies on industry and geographical diversification, I will have a much larger sample dataset available for analysis and this will also include fund specific attributes data like PE investments into specific geographical locations in addition to performance metrics data. One of the key additions to the analysis is that data is now available detailing the different geographical locations that PE funds are investing into. This data is crucial in the development of the country count (ctry_count) variable which is the main effect independent variable that establishes the relationship between geographical diversification and PE fund returns. In this aspect of data collection, Preqin demonstrates an edge over Burgiss and Pitchbook which does not provide similar data granularity. The country count variable (ctry_count) will track the number of geographical locations that the PE funds in the sample data set will invest into. I will be able to assess the extent of the geographical diversification of the PE funds in the sample set. In terms of industry diversification, the data set provides information on whether the PE funds' investments consist of diversified industries or focus industries with the identity of the focus or concentration industries being specified by qualitative text. The availability of this data is important because an interaction variable can now be developed to determine if PE funds that have diversified industry investments are in an advantageous position to handle limited attention issues associated with geographical diversification. Academic and industry studies have both mention the impact of industry expertise in generating superior PE performance and returns. This interaction variable will be crucial in obtaining the result for the proposed hypothesis three (H3) of the study.

Data collected by Preqin is based on a voluntary and self-reporting basis by the GPs of the PE funds. There are occurrences where the respective PE fund data collected do not show the Net IRR, multiple or DPI data. For data sets which do not present performance metrics, these entries will not be included in the analysis.

PE funds data is obtained using a search and filtering function from the Preqin platform. Once the required data sets have been identified and sourced from the platform, it is imported into a separate excel file and subsequently converted into a format for data analysis using STATA software for analysis and regression modelling. This process avoids manual data entry or hand collection methods are prone to human errors.

I will utilize empirical methods and evaluate data using quantitative methods which will involve Ordinary Least Squares (OLS) and 2 SLS instrument variable multivariate regression model analysis. An OLS multivariate regression model will be the main statistical technique use to test the proposed hypotheses in the study and an instrument variable 2 SLS regression model will be used for robust testing. The multivariate regression model will utilize 3 different dependent variables as the proxies for PE fund returns. These dependent variables will include the Net Internal Rate of Return (IRR), multiple or TVPI (total value over paid in) and DPI

(Distributions over paid in). These performance metrics will measure the returns of the PE funds through the cash distributions that GPs provide to investors or LPs as a result of deal realizations, investment exits or dividend distributions. The multiple or TVPI is a ratio which compares the cash distributions of the PE fund and the residual value of the PE fund compared to the initial investment to the fund or GPs provided by the investors or the LPs. In recent times, GPs have been using DPI (Distributions over paid in) which tracks the PE funds' cash distributions on a present value basis back to their LPs over the initial investment capital provided. The DPI provided in the Preqin database is an index in percentage terms where a DPI above 100 percent indicates outperformance by the PE fund. This performance metric will provide a real time tracking of cash distributions by the PE funds to the LPs which are often represented as the performance track record of the PE funds during capital raising exercises or in negotiations of the Limited Partnership Agreement (LPA) terms between LPs and GPs. Another metric called the RVPI which is the residual value over paid investment focuses on the residual value of the portfolio companies or assets held by PE funds. It is visible at the early stages of the investment horizon where distributions from PE funds to the LPs have not yet commence and consist mainly of the valuation of portfolio assets. The multiple or TVPI is the summation of the RVPI and DPI. As GPs commence distributions back to LPs, the DPI metric becomes influential and provide a more current assessment of PE performance. At the end of the horizon, TVPI comprises entirely of DPI. Diagram 4 in the appendix shows TVPI metric during a PE investment horizon.

[Insert Diagram 4 here]

Net IRR as a performance metric has been used in past PE studies but it is now facing scrutiny by PE practitioners due to its reinvestment rate assumption as this can potentially lead to an upward bias in performance measurement in view of the relatively long investment horizon of PE funds. Net IRR as a metric is also affected by the timing of distributions which can be manipulated by GPs to window dress performance during fund raising periods. These criticisms on the reinvestment assumption and possible manipulation of the Net IRR metric because of the timing element has also been discuss in Sorensen and Jagannathan (2015). For these reasons, I will prioritize the two other performance metrics, the multiple and DPI when evaluating empirical results and statistical tests. Rudin, Mao, Zhang and Fink (2019) mentions TVPI becoming a popular metric for PE programs used by industry consultants.

I will use another performance metric known as the Public Market Equivalent (PME) in addressing the alternative explanations in the discussion section of the paper. PME is calculated using the cash flow distributions from the PE funds to the LPs over the cash distributions by comparable publicly listed indices. This performance metric enables PE funds to be evaluated on a risk adjusted basis relative to public indices. This performance metric enables the replication of an investment into a private market security by using a comparable publicly listed index which can be invested and sold at the same time horizon as the private market security. A PME ratio of more than 1 implies that the private market investment has outperformed the comparable publicly listed benchmark during the time horizon. PME does have its critics in that it lacks the mechanism to correctly adjust high beta assets when these outperform publicly listed indices according to Korteweg and Nagel (2016). The PME has also been criticised by Korteweg and Nagel (2016) to have discrepancies with Net Present Value (NPV) appraisal technique with PME overstating NPV by 42 percentage points. Sorensen and Jagannathan (2015) mention a limitation of PME as being more suited as an ex-post measure rather than an ex-ante measure. Despite these limitations, PME is still considered an established metric which incorporates a risk element for PE performance evaluation.

The multivariate regression model will include several independent variables which have been selected based on their effectiveness as individual explanatory variables in past research. These include natural log function of fund size, fund age and top quartile performance classification. The main effect independent variable of interest in the regression model will be the country count variable (ctry_count) as this will be the explanatory variable to proxy for the effects of geographical diversification. The student's t statistics for this main effect variable will allow the study to either accept or reject hypothesis one (H1) proposed in the study at the 10 percent, 5 percent or 1 percent significance levels. I will also include interaction variables which will interact the main effect independent variable (ctry_count) with the other individual independent variables which will include fund age (fundage_ctrycount) and industry diversification (diverseIndust_ctrycount). The student's t statistics for these interaction variables will also be computed to either accept or reject hypothesis two (H2) and Hypothesis three (H3) of the study.

To assess hypothesis four (H4), I will use the baseline regression model with only individual independent variables and include both the main effect country count variable (ctry_count) which proxies for the effect of geographical diversification and the quadratic or square function of ctry count which is known in the regression model as ctry_count2. To demonstrate that the relationship between geographical diversification and PE fund returns follow an inverted U shape function, I will need to show positive coefficients for ctry_count and negative coefficients for ctry_count2 in the regression results. Student's t statistics will again be used to test for the significance for the ctry_count and ctry_count2 variables for all three dependent variables.

The regression model will include controls for strategy fixed effects for the different PE strategies which can include buyouts, growth, fund of funds, co-investments and secondaries. The regression analysis will control for vintage years fixed effects to account for the different vintage years of the PE funds. As the study involves a global PE fund dataset, the regression model will control for the effects of developed and emerging markets by using a region effects dummy variable (region) where North America, Europe and Australasia will be classified as developed markets using the dummy variable region while South America, Africa and Asia will be classified as emerging markets. This control variable is necessary as Klonowski (2019) find PE investments in emerging markets demonstrating superior returns compared to PE investment in developed markets.

<u>Endogeneity Problem</u>

Robust testing procedures will be implemented to treat the endogeneity problem in the OLS multivariate regression model. The concern with the endogeneity issue is that the main effect independent variable country count (ctry_count) may not be the only variable which is influencing the variation of PE fund returns and that there are other factors which may affect PE fund returns through its influence on the country count variable. The presence of endogeneity in a model will result in biased and inconsistent estimates from an ordinary least squares (OLS) regression model.

I will treat the endogeneity issue by using instrument variable analysis and 2 SLS regression referencing the study by Ewens and Marx (2017). Implementing a successful instrument variable analysis can present a significant challenge as the instrument variable will have to satisfy the exclusion restriction condition. A suitable instrument variable can only affect the dependent variable in the model through its effect on the main effect independent variable, specifically the country count variable (ctry_count) used to proxy for geographical diversification. In order not to violate the exclusion restriction condition, the instrument variable should not affect the dependent variable which is the performance metric of PE funds in the study through any other channels.

Once a suitable instrument variable has been selected, the study will conduct an instrument variable 2 SLS regression analysis. This procedure will show the results of the first stage regression as well as the coefficients and z statistics of the instrument variables in the second stage regression. The selected instrumental variable must show a significant student's t test either at the 5 percent or 1 percent significance level in the first stage regression results. The 2 SLS regression output will also be required to present significant z statistics results for the main effect country count variable (ctry_count) that will further reinforce the proposed hypothesis (H1) which states that geographical diversification as proxied by the ctry_count variable will have a negative correlation with PE fund returns. I will use the Durbin and Wu Hausman tests to identify the presence of endogeneity in the regression model and present a first stage regression summary statistics table as part of the robust testing process. If the F statistic in the first stage regression summary statistics table and the minimum eigenvalue statistic calculated is larger than all the figures shown in the 2 SLS relative bias estimates table, this will indicate successful treatment of the endogeneity issue and reject the null hypothesis that the instruments in the regression model are weak. The alternative hypothesis that the instruments used in the model are valid and can be accepted.

After reviewing several instrument variable candidates, I will use the stock market capitalization value as a percentage of GDP of the host country where the PE funds are based in or have their headquarter office as the instrumenting variable for the 2 SLS regression model. The presence of a large and credible stock market where PE funds are based in or have their headquarter office can impact the PE funds' geographical diversification efforts and have an influence on the geographical diversification decision. This is because a PE fund with headquarters in a host country with a larger stock market capitalization will have access to relatively more investment opportunities in its immediate vicinity and this will provide a strong disincentive for the PE fund to pursue geographical diversification efforts. Past studies by Nahata Et al. (2014) and Salehizadeh (2005) find that the stock market attributes of target markets in emerging and developed countries can explain private capital activity. Jeng and Wells (2001) also consider initial public offering (IPO) value and stock market capitalization growth as possible determinants of private market investment activity.

The host stock market capitalization value is taken as a percentage of GDP to control for the different sizes of the host country economies. To satisfy the exclusion restriction condition, I will have to argue that the host stock market capitalization instrument variable does not affect the dependent variable directly or through any other channels except through the geographical diversification decision which is proxied by the main effect country count variable (ctry_count).

I also argue that because a long period of time has elapsed between the assessment period of the PE funds in 2019 and the time period where the host stock market capitalization value is obtained which is the vintage year of the of the PE fund, it is therefore unlikely that the host stock market capitalization value will have an impact on PE fund returns. PE funds typically have 10-year vintage periods which can also be extended by a further 5 years if the GP receives approval for an extension.

In addition to the qualitative argument relating to the time element, the exclusion restriction condition can also be shown to have been satisfied by demonstrating that the host stock market performance, as observed by the host stock market returns has no significant effect on PE fund returns as seen by the study done by Bernstein (2015). Bernstein (2015) developed a "Placebo" test in the study and demonstrated that the two-month fluctuations of the NASDAQ stock market is related to the innovation progress of the firm only through the initial public offering (IPO) completion decision and not through other channels. The methodology shows that by holding the ownership choice constant, NASDAQ stock fluctuations and returns has no significant effect on the long run innovation of the firms.

Both qualitative arguments and the quantitative based approach used in the study by Bernstein (2015) will be utilized to satisfy the exclusion restriction conditions required to prove the suitability of the selected instrumenting variable.

Summary descriptive statistics of model variables

I provide descriptive statistics of the various independent and dependent variables which will be used in the multivariate regression model. The summary descriptive statistics will highlight the differences in fund attributes and performance between PE funds that invest in one geographical location known as single geographic PE funds and PE funds that invest in multiple geographical locations which will be categorized into multi geographic PE funds. For the purposes of this study, multi geographic PE funds will invest in more than 3 geographical locations based on feedback from the GPs of PE funds that invest in the Asia Pacific region. Geographical locations that include countries like Australia and New Zealand are often categorized into one location and this is also seen for cases that includes Hong Kong, Taiwan and mainland China. I will provide the definition that a multi geographic PE fund is one that will invest in more than 3 geographical locations for the analysis required in the study.

I provide summary descriptive statistics in Table 1, Panels A to M in the appendix section of the paper.

[Insert Table 1 here]

The summary descriptive statistics in Panels A and B illustrates that single geographic PE funds are older compared to 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 pronounced with single geographic PE funds being 3.5 years older than multi geographic PE funds. In terms of fund size, the summary statistics in Panel B shows that multi geographic PE funds being larger compared to single geographic PE funds with 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 even more evident at the 75th percentile level with multi geographic PE funds being twice as large at around USD 1.5 billion compared to single geographic PE funds at USD 750 million. Past studies on PE performance have alluded to the diseconomy of scale issue where larger PE funds have underperform in terms of returns as compared to smaller PE funds. In addition, older and more established PE funds have been observed to achieve superior performance as compared to the newer, younger and less established PE funds. The summary descriptive statistics presented provide further support that the multivariate regression model will have to include both fund size and fund age as control variables to take these factors into consideration.

The summary descriptive statistics presented in Panels C and D show the distribution of the country count (ctry_count) variable and the top quartile classification variable. The median or 50th percentile for multi geographic PE funds in 6 different locations showing that the median funds in the sample that have a multi geographic strategy are pursuing extensive geographical diversification. I will show in the empirical analysis section using graphical analysis that PE returns are on a downward trajectory with extensive geographical diversification. The descriptive statistics for top quartile classification do not provide informative value as a dummy variable is used for this analysis but I have included the descriptive statistics for completeness.

The summary descriptive statistics presented in Panels E, F and G show that single geographic PE funds outperform multi geographic PE funds as a group using all 3 dependent variables to proxy for PE fund returns and the results are most evident when DPI is used a performance metric. Mean statistics for all 3 dependent variables use to proxy for PE performance show that single geographic PE funds perform favourably compared to multi geographic PE funds.

The data in Table 2 in the appendix section shows the difference in the mean DPI of the single geographic PE funds and multi geographic PE funds.

[Insert Table 2 here]

The difference in the mean DPI statistic between the two groups is also significant at the 5 percent level with a student's t statistic figure of 2.2348 for a one tailed student's t statistic test. The DPI performance metric which is emerging as an important performance metric used by both GPs and LPs for PE performance evaluation clearly indicates that there is a significant difference in the performance of single geographic PE funds and multi geographic PE funds and provides further evidence that excessive geographical diversification in PE funds can result in limited attention issues and more importantly an adverse impact on PE fund returns.

<u>Summary descriptive statistics of PE fund strategies</u>

The three major PE fund strategies included in the study which are considered as important strategies to 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 in portfolio firms as well as the degree of value creation that is required by the GPs for successful investment exits. PE buyouts involve the majority acquisition of either private or publicly listed companies by PE funds which is then followed by significant restructuring of internal operations and repositioning of the assets of portfolio firms to implement value creation strategies. These value creation strategies enable a higher valuation for the portfolio firm can be achieved when the PE fund exits from the investment. GPs involved in buyouts focus significant time and effort on margin improvement and revenue growth initiatives to increase the exit multiples of portfolio companies. PE funds undertaking growth strategies target mature companies that require one or two additional funding rounds to reach an investment exit either through an initial public offering (IPO) or a trade sale. PE funds pursuing growth strategies which is also known as pre-IPO strategies may make some improvements to the portfolio firms but these firms are mostly at the final stages of reaching an exit or liquidity event and the effort expended by the GPs are not as extensive as compared to buyout PE fund strategies. Fund of funds are typically managed by Limited Partners (LPs) which invest in PE funds managed by GPs. The skillsets required for fund of funds PE strategies differ considerably from buyouts and growth funds and involve LPs carrying out due diligence and background checks on the GP management teams and their track record in managing past PE fund vintages that were able to make profitable cash distributions to investors or LPs.

Panels H, I and J in Table 1 illustrates the summary statistics of the three different PE fund strategies using the performance metrics which includes multiple (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 the three PE performance metrics of multiple, 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 mean IRR at 16.50 compared to mean IRR of 15.76 for growth funds and 11.65 for fund of funds respectively. Fund of funds PE fund strategies demonstrate the lowest performance figures compared to the other two strategies. It is known that fund of funds strategies involves the least amount of active management by GPs and this could potentially shield PE fund of funds from the limited attention issue when pursuing geographical diversification as compared to buyout PE funds which require more active management by GPs. I will review summary statistics of buyout funds, growth funds and fund of funds that are both single geographic and multi geographic PE funds.

To study how geographical diversification can affect PE fund strategy returns, panels K, L and M illustrates 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. The results for PE funds pursuing buyout strategies are consistent with the main hypothesis in the study that PE funds pursuing geographical diversification will face limited attention issues and experience an adverse impact on returns. Single geographic buyout PE funds outperform multi geographic buyout funds both on a multiple and DPI basis with single geographic buyout funds achieving mean multiple of 1.73 versus a mean multiple 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 as compared to 111.46 for multi geographic buyout PE funds. The summary descriptive statistics for growth funds also mirror the same outcome to that of buyout PE funds with single geographic growth funds outperforming multi geographic growth funds both from a multiple 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 multiple as a performance metric but the performance differential is very marginal with multi geographic fund of funds achieving a mean multiple of 1.60 versus the 1.56 mean multiple of single geographic fund of funds. However, from a DPI performance metric basis, the pattern reverts back to single geographic fund of funds having a performance edge over multi geographic fund of funds, achieving a mean DPI of 91.84 versus the mean DPI of 77.05 for multi geographic fund of funds. It is known from an industry standpoint that a fund of funds strategy involves less involvement by GPs compared to buyout and growth funds which require more monitoring, management and governance support efforts from GPs. Due to the impact that different PE strategies can have on PE fund returns, I will also include controls for fund strategy effects in the regression models.

Before reviewing empirical results of the regression models, I analyze correlation data of the model variables which is shown in exhibit 1 in the appendix.

[Insert Exhibit 1 here]

The data in the correlation matrix in exhibit 1 indicates that there are no major issues with the variables in the model that are highly correlated with each other. An exception to this observation is the correlation between the log function of DPI and fund age which shows a correlation figure of 0.6140. Another observation showing high correlation figure is the correlation between the natural log function of multiple and top quartile classification at 0.581. This is to be expected as top quartile classification is given to PE funds that perform well. The low correlation figures shown in the other variables in the correlation matrix suggests that there is a minimal likelihood of multicollinearity being present in the model variables. I review variance inflation factors (VIF) to assess multicollinearity in the model.

Chapter 5 Empirical Results

I discuss the findings of the baseline OLS multivariate regression model using only the individual independent variables and controls based on the figures provided in table 3A in the appendix section. Both the baseline and main multivariate regression models have been developed with the robust option in STATA to treat for heterskedascity issues. This is due to a test for heteroskedascity using the Breush Pagan test (Chi square statistic=19924.57 and p value=0.00000) for the baseline regression model and (Chi square statistic=19961.39 and p value=0.0000) for the main regression model which have indicated the presence of heteroskedascity in the models.

The figures in Table 3A which shows the negative coefficients for the ctry_count variable for all three dependent variables which indicates that there is a negative correlation between geographical diversification and PE fund returns.

[Insert Table 3A here]

These findings are significant at the 1 percent significance level for multiple (t stat=-2.94) and DPI (t stat=-2.99). The findings also support past findings of performance persistence in PE funds as highlighted by the positive coefficients and significant students t statistics for the top quartile variable. Significant results are obtained for all 3 dependent variables at the 1 percent significance level for Net IRR (t stat=27.45), multiple (t stat=56.33) and DPI (t stat=32.86).

An interesting finding is the positive correlation between fund age and PE fund returns which highlights that established and experienced PE funds will outperform less experienced PE funds. The findings show this to be pervasive using all 3 dependent variables and significant at the 1 percent level (Net IRR:t stat=3.40, multiple: t stat=7.83 and DPI: t stat=10.81). In addition, the model results indicate industry diversification by PE funds has a significant impact on PE fund returns as seen from the positive coefficients of the diverse_Indust variable and significant students t statistics for multiple (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 recently Huss and Steger (2020) on the positive impact that diverse industry expertise in PE funds can have on returns. Industry diversification unlike geographical diversification has a positive impact on PE fund returns which may be attributable to the lower costs and higher benefits involve for PE funds to have diversified industry investments compared to being geographically diversified.

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

[Insert Table 3B here]

The main effect country count variable (ctry_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), multiple (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 that for PE funds pursuing geographical diversification. The results for the main effect independent variable for geographical diversification (ctry_count) are thus consistent with the findings of the baseline regression model in table 2A. In addition, referencing ctry_count summary descriptive statistics from Panel C, mean IRR data from Panel G and the main regression model output in Table 3B in the appendix, a one standard deviation increase in geographical diversification proxied by ctry_count will lead to 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 ctry_count of multi geographic funds * coefficient of ctry_count / mean of multi geographic fund Net IRR. This will provide the following result after making the necessary calculations: 3.08 * (-0.981) / 16.10 = -18.8 percent. For multiple, due to the natural log treatment, I apply the following calculation: [Exp (0.012)-1] * 100 * 3.08 = 3.72 percent. The methodology for the calculation is taken from a publication from UCLA[5].

I reinforce an established finding in past PE studies on the performance persistence of top quartile funds. The top quartile classification variable in the regression model shows positive and significant coefficients at the 1 percent significance level for all three dependent variables (t stat=27.45 for IRR; t stat=56.27 for multiple; t stat=32.74 for DPI).

A control variable in the regression analysis which has provided some interesting observations is the diverse industry (diverseIndust) variable where the student's t statistics for this control variable indicate that PE funds which invest in diversified industry sectors has a positive coefficient and is significant at the 1 percent level for DPI (t stat=3.16) and also shows positive coefficient for multiple. This finding supports the earlier findings of Lossen (2006), Humphery-Jenner (2013), Huss and Steger (2020) and Bowden Et al. (2016) with these past studies mentioning that PE returns increases as PE funds have diverse industry or sector expertise. This finding however does not support the earlier arguments made by Bygrave (1987) and Norton and Tenenbaum (1993) which posit that VC funds should pivot towards a specialization strategy to achieve successful outcomes in VC efforts. This is also in contrast to the recent findings by Huss and Steger (2020) which mention that diversification across

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

industries does not result in better returns for PE buyout funds but diversification within industries generate positive returns for buyout PE funds.

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 (fundage_ctrycount) indicates a positive coefficient and is significant at the 1 percent level for Net IRR (t stat=3.01). This finding demonstrates that older, more established and experienced PE funds are able to 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 that the interaction variable of diverse industry and country count (diverseIndust_ctrycount) 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 multiple. PE funds that have industry diversification in their investments or have 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 semi-conductor chip segment will find it difficult to expand its geographical exposure from markets like Taiwan and Korea that has significant presence in the semi-conductor industries to countries in the Southeast Asia region. Several studies allude to the positive role that having deep and diverse industry expertise will have on superior PE performance. 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 the PE funds.

To assess the overall predictive ability of the regression model, the study computed R square statistics for the model which indicates a figure of 0.182 for Net IRR as a dependent variable. This can also be interpreted by stating that 18.2 percent of the variations of the dependent variable, which in this case is Net IRR can be explained by the independent variables in the regression model. The R square figures computed for multiple as a dependent variable is 0.475 and for DPI as a dependent variable is 0.742 which shows good explanatory power for both models. To assess hypothesis 4 (H4), I use additional regression analysis based on the multivariate regression model results presented in table 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, I will need to obtain a positive coefficient with significant student's t statistic for ctry_count and a negative coefficient with a significant t statistic for the quadratic function of country count (ctrycount2). Referencing Table 3C in the appendix, I show positive coefficients for Net IRR and multiple.

[Insert Table 3C here]

I also show both positive coefficients and significant results for DPI at the 1 percent significance level (t stat=2.56) for the ctry_count variable. This is reinforced with negative coefficients and significant students' t statistics at the 5 percent significance level for the quadratic function of country count (ctry_count2) for Net IRR (t stat=-2.07) and at the 1 percent significance level for multiple (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 shape relationship with geographical diversification. In terms of explanatory power, the model shows R square figures of 0.1931 for Net IRR, 0.475 for multiple and 0.743 for DPI, demonstrating good explanatory power for the model.

I provide graphical analysis using bin scatter graphs to illustrate the relationship between geographical diversification and PE fund returns. The bin scatter and line fit diagrams shown in Figure 5 indicates an inverse relationship between geographical diversification and PE fund returns using dependent variables.

[Insert Figure 5 here]

PE fund returns are on a downward trajectory with extensive diversification into multi geographic locations.

Robust testing and Endogeneity Treatment

I discuss robust testing procedures and endogeneity treatments. To check for multicollinearity issues, I run the variance inflation factor (VIF) tests on the baseline regression models using DPI and multiple as dependent variables. The VIF tests data reveal with the exception of fund age, all other independent variables show a VIF factor of less than 10 which can be interpreted that multicollinearity is not a serious issue for the model. In addition, the coefficient estimates for the main effect independent variable, country count (ctry_count) remains highly significant and provide a VIF reading of 5.8 for the models using DPI and multiple as dependent variables providing assurance that multicollinearity is not an issue.

For the endogeneity treatment, I use an instrument variable which is the value of the host stock market capitalization as a percentage of GDP. Percentage of GDP is included to control for the different sizes of host market economies. In order to ascertain if a natural log treatment is needed for the instrument variable, I use a histogram chart analysis to assess the normality of the instrument variable. The histogram charts of the instrument variable without natural log and with the natural log treatments are shown in figure 6 in the appendix.

[Insert Figure 6 here]

After evaluating the histogram analysis of the instrumenting variable, a natural log treatment will be applied to the instrument variable in the 2 SLS regression model for the endogeneity treatment. Table 4 in the appendix section shows the first stage regression results and second stage regression results of the instrument variable 2 SLS regression.

[Insert Table 4 here]

In the first stage regressions output in table 4 of the appendix section, the instrument variable which is the host stock market capitalization value as percentage of GDP (lnhost_cappctGDP) shows a negative coefficient with students t statistics indicating the results to be significant at the 1 percent level (t stat =-21.07). The data presented in the 2 SLS regression indicates that the instrument variable selected is suitable. The result is consistent with the reasoning that PE funds that are based in or have headquarter office in a host country with a larger stock market capitalization will have access to more opportunities and this provides a strong disincentive for PE funds to undertake geographical diversification efforts. The negative coefficient provided by the selected instrument variable and the significant student's t statistic also supports this argument using regression analysis. I analyze results for the second stage regression. The second stage regression results indicates that the ctry_count variable has a negative coefficient and is significant at the 1 percent level with the corresponding z statistics (z stat =-2.86). This result shows that hypothesis one (H1) which states that there is a negative correlation between geographical diversification and PE returns and that there is a diversification discount for PE funds pursuing geographical diversification can be supported after endogeneity treatments using instrument variable analysis and 2 SLS regression model.

I review first stage regression summary statistics to assess whether the instruments used in the regression model are now valid after the endogeneity treatments. Table 5 in the appendix section shows the results of the first stage regression summary statistics and the robust testing procedures that includes the 2 SLS relative bias table.

[Insert Table 5 here]

The F statistic, F(1,7951) which is shown in table 5 provided an estimate figure of 443.991 which is also reflected as the minimum eigenvalue statistics. This estimate figure of 443.991 is larger than all the estimate figures provided by 2 SLS relative bias table in table 5. Reviewing the figures in table 5, even at the 10% level, both the 2 SLS Size and LIML Size Wald tests are showing estimate figures of 16.38 which is much smaller than the estimate figure of 443.991 provided by the F statistic in the first-stage regression summary statistics. The findings from these tests show that after applying the endogeneity treatments through the instrument variable and 2 SLS regression model, the null hypothesis that the instruments used in the model are weak can be rejected and the alternative hypothesis that the instruments in the model are now valid can be accepted after the endogeneity treatments. I conduct endogeneity tests in the form of the Durbin and the Wu Hausman tests shown in Exhibit 2 in the appendix section.

[Insert Exhibit 2 here]

The p values shown in both tests are larger than 0.05 (Dubin test: p=0.0691; Wu-Hausman test: p=0.07) which indicates that the presence of endogeneity is not detected in the model after treatment.

I provide a quantitative argument to support the exclusion restriction condition requirement by using the methodology demonstrated by Bernstein (2015) where a "Placebo" test in the study demonstrated that the two-month fluctuations of the NASDAQ stock market is related to the innovation progress of the firm only through the initial public offering (IPO) completion decision and not through other channels. Referencing Bernstein's methodology, I obtain host stock market returns in the vintage year where the PE fund has established a headquarter office in the host market as a variable of interest. I apply a natural log treatment to the variable which is classified as the variable name of (ln_hoststockmkt_return). I run a regression of this variable (ln_hoststockmkt_retrn) against the dependent variable (lnDPI) to demonstrate that the instrument variable affects the main effect independent variable (ctry_count) only through the geographical diversification decision and not through any other channels. This can be proven if both the host stock market returns variable (ln_hostockmkt_retrn) and dependent variable (lnDPI) for the model are not correlated to each other in the regression analysis consistent with the “Placebo” test by Bernstein (2015).

The data in Exhibit 3 in the appendix section which shows the regression analysis results indicates that there is no correlation between the returns of the host stock market and PE fund returns through the dependent variable DPI which is used to proxy for PE fund performance with the student’s t statistic being insignificant (t=0.26).

[Insert Exhibit 3 here]

This further supports the exclusion restriction condition in addition to the qualitative argument provided earlier which states that a significant period of time has elapse between the vintage year of the PE fund where the host stock market capitalization value is obtained and the assessment year for PE fund returns to be measured. I show a comparison of the coefficient estimates, students’ t statistics and z statistics in OLS regression, first stage and the 2 SLS regression analysis in Table 6 in the appendix.

[Insert Table 6 here]

The coefficients and z statistics in the 2 SLS regressions for both DPI and multiple in table reinforce the main finding that there is negative correlation between geographical diversification and PE fund returns and results are significant for multiple and DPI at the 1 percent level using OLS and 2 SLS regression methods.

Chapter 6 Discussion

I discuss possible alternative explanations in this section for the study findings which shows PE funds with geographical diversification has a negative correlation with PE fund returns. An alternative explanation is that PE funds which are geographically diversified are more conservative compared to single geographic PE funds and hence will demonstrate lower PE returns. However, this does not imply that multi geographic PE funds adopt a more conservative approach compared to single geographic PE funds. There are some multi geographic PE funds that invest in frontier markets like the Sub Saharan African region or emerging Latin American regions which are highly risky investments as compared to single geographic PE funds that invest in developed single geographic locations like Australia, New Zealand, Canada, Brunei, Hong Kong and Taiwan.

I will also address this issue using an additional multivariate regression model which will use the Public Market Equivalent (PME) as a dependent variable. Unlike the dependent variables used in the study which includes the IRR, multiple and DPI, the PME 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 not geographically diversified. Due to Preqin having a limited sample of PME data, only about 1600 observations are available for analysis and coverage is for newer vintage PE funds from 2003.

I address an alternative explanation that PE funds that have more investment staff resources or manpower on the ground will be able to cope with demands of geographical diversification. I obtain investment staff numbers but at the parent firm level of the PE funds which is recently available from Preqin. I will develop an interaction variable of invest staff and country count (ctry_count) to assess if 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:

Yi = constant + X_1 (ctry_count) + X_2 (natural log of fund size) + X_3 (fund age) + X_4 (top quartile performance classification) + X_5 (invest staff) + X_6 (diverse industry) + X_7 (invest staff x ctry_count) + ε

Where Yi is the performance return of PE funds using PME to incorporate risk adjustments.

I review histogram charts for the PME with and without the natural log treatments which I show in Figure 7 in the appendix.

[Insert Figure 7 here]

After reviewing the histogram analysis, I employ a natural log treatment for PME due to its bell curve distribution for use in the model.

Referencing the regression output results in Table 7, the main effect independent variable country count (ctry_count) is significant at the 10 percent significance level with a negative coefficient (t stat=-1.90). This result again indicates that geographical diversification is negatively correlated with PE fund returns and there is a diversification discount. Hypothesis one (H1) of the study is still supported 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 to 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 show that the interaction variable of investment staff and geographical diversification (invest_staff x ctry_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 cope better with the adverse effects of geographical diversification.

[Insert Table 7 here]

Another alternative explanation for multi geographic PE funds showing lower returns can be attributed to the higher setup and operational costs of multi geographic PE funds vis-à-vis single geographic PE funds. Multi geographic PE fund operations involve a larger number of offices and hire more investment professionals and support staff due to their larger geographical footprint. Investment due diligence costs will involve higher expenditure for multi geographic PE funds due do the additional travel requirements involved in pursuing PE deals in multiple geographic locations. A possible empirical analysis in the future will be to obtain the expense ratios of both single geographic and multi geographic PE funds and utilize this data as a control variable in the model. However, this data is currently not available in the Preqin database. An alternative procedure will be to use fund formation costs to proxy for operational costs although this is not considered an ideal data substitute as it focuses more on upfront costs instead of ongoing operational costs. A review of the Preqin PE database has reveal very few observations of this data in the platform. It is likely that other secondary PE databases may not have this data as it is proprietary information. This analysis may require the support of LPs and is a potential area of future research.

I provide an industry angle through feedback from senior PE executives on the main findings of the study. Initial feedback has been encouraging with an appreciation of the novel aspects of the findings using robust methodology. The summary of the industry feedback is provided in table 8 of the appendix and I include case studies of PE funds for real world perspectives.

[Insert Table 8 here]

Chapter 7 Conclusion

This study examines the impact of geographical diversification on the returns of global PE funds, an area of PE research which has not been given due attention in past studies. Using a sample set of approximately 8000 global PE funds and multivariate regression analysis, findings show that there is a negative correlation between geographical diversification and PE fund returns. The findings from the main regression model indicate significant results for all 3 dependant variables 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 will result in an 18.8 percent reduction in PE fund returns from a Net IRR perspective.

In addition, fund age and industry diversification in PE funds mitigates the negative correlation between geographical diversification and PE fund returns. The relationship between geographical diversification and PE fund returns follows an inverted U shape relationship where PE funds that engage in excessive geographical diversification will experience adverse impact on returns after reaching an inflexion point.

I reinforce established findings in past studies on the performance persistence of PE funds. A further insight obtain is the positive relationship observed between PE fund age and returns highlighting that older, more experienced PE funds outperform younger or newer PE funds. Graphical analysis also indicates a downward trajectory in returns when PE funds pursue extensive geographical diversification.

I use an instrument variable analysis and 2 SLS regression model for endogeneity treatments. Results reveal success in treating the endogeneity issue. The coefficients for the main effect geographical diversification variable from both OLS and 2 SLS regression analysis methods are consistent in sign and are significant at the 1 percent level. Empirical analysis using the Public Market Equivalent (PME) provide reinforcement of the main findings and address the alternative explanation that multi geographic PE funds underperform due to risk aversion and conservatism. PME model indicates that PE funds with additional investment staff resources on the ground can cope with the adverse effects of geographical diversification. A future area of research is to obtain fund operating expense data to address an alternative explanation that multi geographic PE funds generate lower returns due to higher cost structure.

References

Acharya, Gottschalg, Hahn and Kehoe, 2012. Corporate governance and value creation: evidence from private equity. Rev. of Financ. Stud. 26, 2, 368-402.

Achaya, Kehoe and Reyner, 2009. Private Equity vs PLC Boards in the UK: A comparison of practices and effectiveness. J. of Applied Corp. Financ. 21, 1, 45-57

Agrawal and Tambe, 2015. Private equity and workers' career paths: The role of technological change. Rev. of Financ. Stud. 29, 9, 2455-2489

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

Arjun Sethi, Sovereign Wealth Funds, Private Equity Funds, and Financial Markets, 2008. J. PE. 11, 4, 12-27

Bernile, Cumming and Lyandres, 2007. The size of venture capital and private equity fund portfolios. J. of Corp. Financ. 13, 564-590

Bernstein, Giroud and Townsend, 2016. The impact of venture capital monitoring. J. Financ. 71, 4, 1591-1621

Bernstein, 2015. Does going public affect innovation? J. Finance. 70, 4, 1365-1403

Bernstein and Sheen, 2016. The operational consequences of private equity buyouts: evidence from the restaurant industry. Rev. of Financ. Stud. 29, 9, 2387-2418

Bernoff and Colavecchio, 2014. The macroeconomic determinants of private equity investment: A European comparison. Applied Econ. 46, 11, 1170-1183

Bain, 2021. Global private equity report 2021. 1-76

Black and Gilson, 1998. Venture capital and the structure of capital markets: banks versus stock markets. J. Financ. Econ. 47, 3, 243-277

Bloom, Sardin and Van Reebannen, 2015. Do private equity owned firms have better management practices? American Economic Review: Papers and proceedings. 105, 5, 442-446

Bortolotti, Fotak and Megginson, 2015. The sovereign wealth fund discount: evidence from public equity investments. Rev. of Financ. Stud. 28, 11, 2993 – 3035.

Braun, Jenkinson and Stoff, 2016. How persistent is private equity performance? Evidence from deal level data, J. Financ. Econ. 123, 273-291

Braun, Jenkinson and Schemmerl, 2019. Adverse selection and the performance of private equity. J. Financ. Econ. 136, 1, 44-62

Brown, Hu and Zhang, 2021. The evolution of private equity fund value. J. Alternative Investments. 23, 4, 11-28

Bucher, Mohamed and Schwienbacher, 2016. Does risk explain persistence in private equity performance? J. Corp Financ. 39, 18-35

Bucher, Mohamed and Schwienbacher, 2017. Diversification, risk and returns in venture capital. J. Business Venturing. 32, 519-535

Butt, Shivdasani, Stendevad and Wyman, 2008. Sovereign wealth funds: A growing global force in corporate finance. J. Applied Corp. Financ. 20, 1, 73-83

Brown and Kaplan, 2019. Have private equity returns really declined? Kenan Institute of private enterprise report. 1-12

15 Bowden, Harjoto, Paglia and Tribbit, 2016. The impact of diversification on private equity fund returns. J. Global Business Management. 12, 1, 49-66

Bygrave, 1987. Syndicated investments by venture capital firms: A networking perspective, Journal of business venturing. 2, 139-154

Cochrane, 2005. The risk and return of venture capital. J. Financ. Econ. 75, 3-52

Cavagnaro, Sensoy, Wang and Weisbach, 2019. Measuring institutional investors' skill at making private equity investments, J. of Financ. 74, 6, 3089-3134

Cambridge Associates, 2014. Declaring a major: sector-focused private investment funds. Research note, Cambridge associates. 1-13

Chemmanur, Krishnan and Nandy, 2011. How does venture capital financing improve efficiency in private firms? A look beneath the surface. Rev. of Financ. Stud. 24, 12, 4037-4090

Chemmanur, Loutskina and Tian, 2014. Corporate venture capital, value creation and innovation. Rev. of Financ. Stud. 7, 8, 2435-2473

Cressy, Malipiero and Munari, 2007. Playing to their strengths? Evidence that specialization in the private equity industry confers competitive advantage. J. Corp. Financ. 13, 647-669

Cressy, Malipiero and Munari, 2012. Does VC fund diversification pay off? An empirical investigation of the effects of VC portfolio diversification on fund performance. International Entrepreneur Management Journal. 10, 139-163

Corwin and Coughenour, 2008. Limited attention and the allocation of effort in securities trading. J. Finance. 62, 6, 3031-3067

Cumming, Fleming, Johan and Takeuchi, 2010. Legal protection, corruption and private equity returns in Asia. J. of business ethics. 95, 173-193

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

Cumming and Dai, 2009. Local bias in venture capital investments. J. Empirical Financ. 17, 362-380

Cumming and Na Dai, 2010. Fund size, limited attention and valuation of venture backed firms, J. of Empirical Financ. 18, 2-15

Cumming and Zambelli, 2012. Private equity performance under extreme regulation. J. of Banking and Financ. 37, 1508-1523

De-Silanes, Phalippou and Gottschalg, 2015. Giants at the gate: Investment returns and diseconomies of scale in private equity. J. Financ. Quant. Anal. 50, 3, 377-411

Demaria, 2020. Introduction to private equity, debt and real assets: From venture capital to LBO, senior to distressed debt, immaterial to fixed assets. 3, 109-114

Demaria, 2015. Fee levels, performance, and alignment of interests in private equity. J. Alternative Investments. 17, 4, 95-135

Dewenter, Han and Malatesta, 2010. Firm values and sovereign wealth fund investments. J. Financ. Econ. 42, 256-278

Engel and Keilbach, 2007. Firm level implications of early state venture capital investment – An empirical investigation. J of Empirical Financ. 14, 50-167

Ewens, Michael, Jones and Rhodes-Kropf, 2013. The price of diversifiable risk in venture capital and private equity. Rev of Financ. Stud. 26, 1854-1889

Ewens and Marx, 2018. Founder replacement and startup performance. Rev. of Financ. Stud. 31, 4, 1532-1565

Faccio and Hsu, 2017. Politically connected private equity and employment. J. finance. 72, 2, 539-574

Fang, Ivashina and Lerner, 2015. The disintermediation of financial markets: Direct investing in private equity. J. Financ. Econ. 116, 160-178

Franzoni, Novak and Phalippou,2012. Private equity performance and liquidity risk. J. Financ. 67, 6, 2341-2373

Fulghieri and Sevilir, 2009. Size and focus of a venture capitalist portfolio. Rev. of Financ. Stud. 22, 11, 4643-4680

Fung, Hsieh, Naik and Ramadorai, 2008. Hedge funds: Performance, risk and capital formation. J. of Financ. 63, 4, 1777-1803

Fung and Hsieh, 2004. Hedge fund benchmarks: A risk based approach. Financ. Anal. J. 60, 5, 65-80

Gasparro and Pagano, 2010. Sovereign wealth funds' impact on debt and equity markets during the 2007-09 financial crisis. Financ. Anal. J. 66, 3, 92-103

Giot, Hege and Schwienbacher, 2014. Are novice private equity fund risk-takers? Evidence from a comparison with established funds. J. Corp. Financ. 27, 55-71

Gompers, Kovner and Scharfstein, 2007. Venture capital investment cycles: The impact of public markets. J. Financ. Econ. 87, 1-23

Gompers, Kovner and Lerner, 2009. Specialization and success: evidence from venture capital. J. Econ. and Management Strategy, 18, 3, 817-844

Gompers, 1996. Grandstanding in the venture capital industry. J. Financ. Econ. 42, 133-156

Guo, Hotchkiss and Song, 2011. Do buyouts create value? J. Financ. 66, 2, 479–517

Gupta and Sapienza, 1992. Determinants of venture capital firms' preferences regarding industry diversity and geographic scope of their investments. J. Business Venturing. 7, 347-362

Harris, Jenkinson and Stucke, 2012. Are too many private equity funds top quartile? J. of Applied Corp, Financ. 24, 4, 77-89

Harris, Jenkinson and Kaplan, 2014. Private Equity performance: What do we know. J. Financ. 69, 5, 1851–1882.

Hellmann and Puri, 2002. Venture capital and the professionalization of start-up firms: empirical evidence. J. Financ. 57, 1, 169-197

Hochberg, Ljungqvist and Jorgensen, 2013. Informational holdup and performance persistence in venture capital. Rev. of Financ. Stud.27. 1, 102-152

Hochberg and Rauh, 2013. Local overweighting and underperformance: evidence from limited partner private equity investments. Rev. of Financ. Stud. 26, 2, 403-451

Hook, Hee and Yook, 2017. An analysis of returns of moderately aged buyout funds with low residual values. J. Alternative Investments. 19, 4, 67-76

Huss and Steger, 2020. Diversification and fund performance – An analysis of buyout funds. J. Risk and Fin. Management. 13, 136

Ilmanen, Chandra, Mcquinn, 2020. Demystifying illiquid assets: expected returns of private equity. J. PE. 23, 4, 8-22

Jeng and Wells, 2000. The determinants of venture capital funding: evidence across countries. J. Corp. Financ. 6, 241-289

Jegadeesh, Kraussl and Pollet, 2015. Risk and expected returns of private equity investments: evidence based on market prices. Rev. of Financ. Stud. 28, 12, 3269-3302

Kandel, Leshchinskii and Yuklea, 2011. VC funds: Aging brings myopia, J. Financ. Quant Anal. 46, 2, 431-457

Kanniainen and Keuschnigg, 2003. The optimal portfolio of start-up firms in venture capital finance. J. Corp Financ. 9, 521-534

Kaplan, Steven N., and Per Stromberg, 2001. Venture capitalists as principals: Contracting, screening and monitoring. American Economic Review. 91, 426-430

Kaplan and Schoar, 2005. Private equity performance returns, persistence and capital flows. J. Financ. 60, 4, 1791-1823

Kotter and Lel, 2011. Friends or foes? Target selection decisions of sovereign wealth funds and their consequences. J. Financ. Econ. 11, 360-381

Kinlaw, Kritzman and Mao, 2015. The components of private equity performance: implications of portfolio choice. 18, 2, 25-38

Korteweg and Sorensen, 2017. Skill and luck in private equity performance. J. Financ. Econ. 124, 535-562

Korteweg and Nagel, 2016. Risk adjusting the returns to venture capital. J Financ. 71, 3, 1437-1470

Klonowski, 2019. Mature and not mature enough: comparing private equity in developed and emerging markets J. PE. 22, 2, 9-18

Lerner and Schoar, 2005. Does legal enforcement affect financial transactions? The contractual channel in private equity. The quarterly J. Econ. 223-246

Lerner, Schoar and Wongsunwai, 2007. Smart institutions, foolish choices: the limited partner performance puzzle. J. Financ. 62, 2, 731-764

Lerner, Ledbetter, Speen, Leamon and Allen, 2016. Private equity in emerging markets: yesterday, today and tomorrow. J. PE. 19, 3, 8-20

Lin Sun and Melvyn Teo, 2018. Public hedge funds. J. Financ. Econ. 131, 44-60

Lu, Ray and Teo, 2016. Limited attention, marital events and hedge funds. J. Financ. Econ. 122, 607-624

Ljungqvist, Richardson and Wolfenzon, 2019. The investment behaviour of buyout funds: theory and evidence. Financ. Management. 49, 3-32

Mark Humphery-Jenner, 2012. Private Equity fund size, investment size and value creation. Rev. of Financ. 16, 799-835

Mark Humphery-Jenner, 2013. Diversification in Private Equity Funds: On knowledge sharing, risk aversion and limited attention. J. Financ. Quant Anal. 48, 5, 1545-1572

Markowitz, 1970. Portfolio selection: efficient diversification of investment, New Haven: Yale university press publication.

Marquez, Nanda and Yavuz, 2014. Private Equity Fund Returns and Performance Persistence. Rev. of Financ. 19, 1783-1823

Matusik and Fitza, 2012. Diversification in the venture capital industry: leveraging knowledge under uncertainty. Strat. Mgmt. J. 33, 407-426

Metrick and Yasuda, 2010. Economics of private equity funds. Rev. of Financ. Stud. 23, 6, 2303-2341

Melvyn Teo, 2009. The Geography of Hedge Funds. Rev. of Financ. Stud. 22, 9, 3531-3561

Melvyn Teo, 2012. The geography of private equity. Private equity insights, Asia Private Equity Institute (APEI). 1-11

Megginson, You and Han, 2013. Determinants of sovereign wealth fund cross border investments. 48, 539-572

Mukherjee and Pareek, 2020. Limited attention and portfolio choice: The impact of attention allocation on mutual fund performance. Financial Management. 49, 1083-1125

Nadauld, Sensoy, Vorkink and Weisbach, 2018. The liquidity cost of private equity investment: Evidence from secondary market transactions. J. Financ. Econ. 132, 158-181

Ndlwana and Botha, 2018. Determinants of private equity investments across BRICS countries. J. PE. 21, 4, 18-28

Nahata, Hazarika and Tandon, 2014. Success in global venture capital investing: do institutional and cultural differences matter? J. Financ. and Quant. Anal. 49, 4, 1039-1070

Norton and Tenenbaum, 1993. Specialization versus diversification as a venture capital investment strategy. J. of business venturing. 8, 431-442

Peng and Xiong, 2006. Investor attention, overconfidence and category learning. J. Financ. Econ. 80, 563-602

Phalippou, 2020. An inconvenient fact: private equity returns and the billionaire factory. Working Paper, University of Oxford: Said Business School. 1-37

Phalippou and Gottschlag, 2008. The performance of private equity funds. Rev. of Financ. Stud. 22, 4, 1747 – 1776

Phalippou, 2009. Venture capital funds: Flow performance relationship and performance persistence. J. Banking and Fin. 34, 568-577

Robinson and Sensoy, 2013. Do private equity fund managers earn their fees? Compensation, ownership and cash flow performance. Rev. of Financ. Stud. 26, 11, 2760-2797

Robinson and Sensoy, 2016. Cyclicality, performance measurement, and cash flow liquidity in private equity. J. Financ. Econ. 122, 521-543

Ross, 1976. The arbitrage pricing theory of capital asset pricing. J. of econ. theory. 13, 341-360

Rudin, Mao, Zhang and Fink, 2019. Private equity program breadth and strategic asset allocation. J. PE. 22, 2, 19-26

Salehizadeh, 2005. Venture capital investments in emerging economies: an empirical analysis. J. Developmental Entrepreneurship. 10, 3, 253-269

Sensoy, Wang and Weisbach, 2014. Limited Partner performance and the maturing of the private equity industry. J. Financ. Econ. 112, 320-343

Sharpe,1964. Capital asset prices: a theory of market equilibrium under conditions of risk. J. Financ. 19, 3, 425-442

Sorensen and Jagannathan, 2015. The public market equivalent and private equity performance. Financ. Anal. J. 71, 4, 43-50

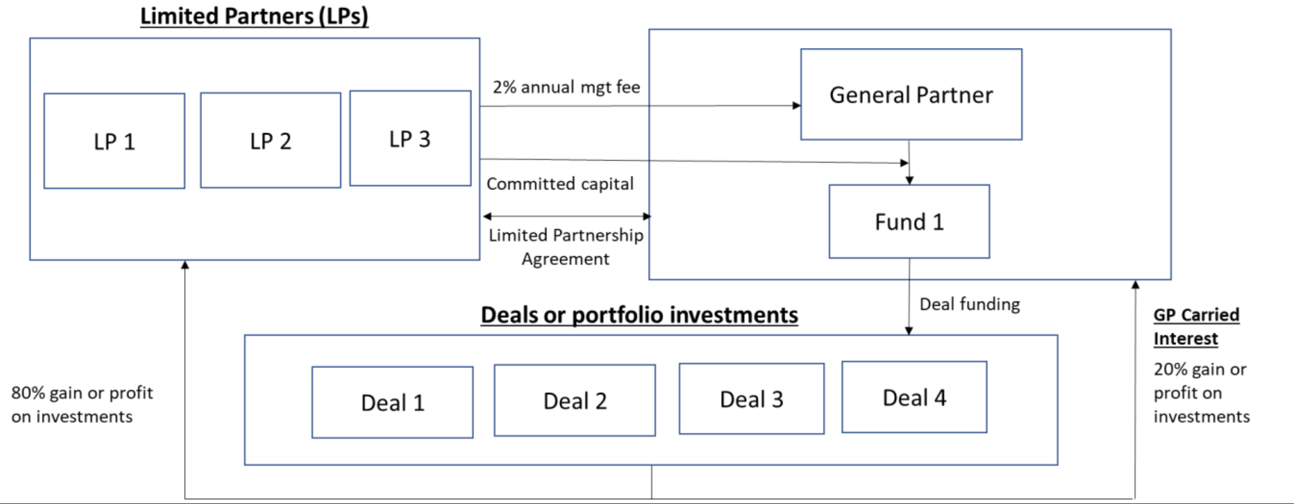
Sun and Liang, 2021. Globalization and affordability of microfinance. J. Business Venturing. 36, 1-18

Ulrich Lossen, 2006. The performance of private equity funds: does diversification matter? Governance and efficiency of economic systems Discussion Paper. 192,

Zhang and Wang, 2015. Limited attention of individual investors and stock performance: Evidence from the ChiNext market. Econ. Modelling. 50, 94-104

Appendix: Supporting data, tables, figures and exhibits

Diagram 1: Investment Structure of Private Equity Funds



Source: Cyril de Maria: Introduction to private equity (3rd edition)

Diagram 2: Top 20 PE firms by capital raised in last 10 years

Rank	Firm	Headquarters	Aggregate Capital Raised in the Last 10 Years ($bn)	Dry Powder ($bn)
1	Carlyle Group	Washington, US	66.7	15.8
2	Blackstone Group	New York, US	62.2	31.9
3	KKR	New York, US	57.9	17.6
4	Goldman Sachs	New York, US	55.6	16.0
5	Ardian	Paris, France	53.4	22.3
6	TPG	Fort Worth, US	47.0	12.9
7	CVC Capital Partners	London, UK	42.2	10.6
8	Warburg Pincus	New York, US	41.6	12.9
9	Advent International	Boston, US	40.9	14.4
10	Bain Capital	Boston, US	37.7	10.0
11	Apax Partners	London, UK	35.8	8.6
12	Apollo Global Management	New York, US	33.1	7.2
13	Hellman & Friedman	San Francisco, US	28.2	10.2
14	HarbourVest Partners	Boston, US	26.2	7.6
15	Silver Lake	Menlo Park, US	21.5	5.1
16	Leonard Green & Partners	Los Angeles, US	21.2	9.5
=	Lexington Partners	New York, US	21.2	7.3
18	Vista Equity Partners	San Francisco, US	20.8	7.3
19	China Reform Fund Management	Beijing, China	19.6	18.9
20	Adams Street Partners	Chicago, US	19.2	6.2

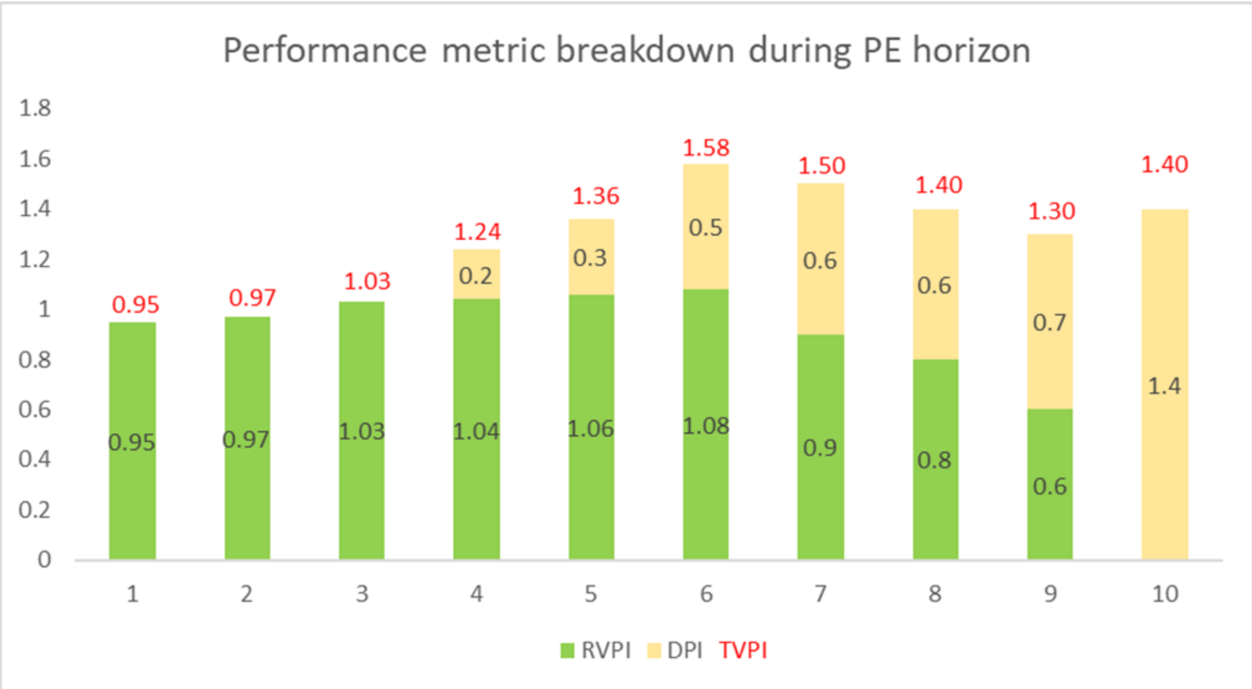
Source: Preqin and figures in USD

Diagram 3: Recent PE and VC successful fund raising activities ranked by fund size

Rank	PE Fund Name	Strategy	Region	Final Close Size ($mn)	Second Close Date	Target Size ($mn)
1	Carlyle Partners VII	Buyout	North America	18,500	6-Feb-18	15,000
2	EQT IX	Buyout	Europe	18,407	31-Dec-20	16,231
3	Vista Equity Partners Fund VII	Buyout	North America	16,000	31-Dec-18	16,000
4	Clayton, Dubilier & Rice Fund XI	Buyout	North America	16,000	1-Sep-20	13,500
5	KKR Asian Fund IV SCSp	Buyout	North America	15,000	1-Oct-20	12,500
6	Lexington Capital Partners IX	Secondaries	North America	14,000	1-Oct-19	12,000
7	Platinum Equity Capital Partners Fund V	Buyout	North America	10,000	1-Nov-19	8,000
8	New Mountain Partners VI	Buyout	North America	9,586	29-Sep-20	8,000
9	Brookfield Capital Partners V	Buyout	North America	9,000	6-Aug-19	7,000
10	Dyal Capital Partners IV	Growth	North America	9,000	3-Apr-19	6,000
11	Dover Street X	Secondaries	North America	8,100	6-Oct-20	5,750
12	Ardian Buyout VII	Buyout	Europe	7,669	30-Apr-20	6,602
13	KKR European Fund V	Buyout	North America	6,478	31-Mar-19	5,692
14	Providence Equity Partners VIII	Buyout	North America	6,040	27-Dec-18	5,000
15	Blackstone Life Sciences V	Venture (General)	North America	4,605	13-May-20	4,600
16	Blackstone Growth	Growth	North America	4,500	15-Jan-21	3,500
17	Welsh, Carson, Anderson & Stowe XIII	Buyout	North America	4,300	30-Mar-19	3,500
18	Hamilton Lane Secondary Fund V	Secondaries	North America	3,900	30-Sep-19	3,000
19	Oak Hill Capital Partners V	Buyout	North America	3,800	2-Apr-19	3,000
20	The Resolute Fund IV	Buyout	North America	3,630	2-May-18	3,630

Source: Preqin and figures in USD

Diagram 4: Constitution of multiple or TVPI performance metric during PE investment horizon



Source: Measuring private equity fund performance: Background Note INSEAD

Table 1: Summary Descriptive Statistics

Summary Descriptive Statistics- Independent Variable

This table reports summary descriptive statistics of the fund age profile of single geographic PE funds and multi geographic PE funds. The PE funds have vintage years starting from 1973 to 2018 and is obtained from Preqin's private equity database.

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 for 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 General Partners (GPs) of the fund. The summary descriptive statistics for fund size does not include any natural logarithm being applied.

	Panel A- Independent variable: Fund Age (yrs)		Panel B- Independent variable: Fund Size (USD '000)	
Descriptive statistic	Single Geographic PE Fund	Multi-Geographic PE Fund	Single Geographic PE Fund	Multi-Geographic PE Fund
N (observations)	7,736	592	7,241	568
Mean	11.41	9.71	924.91	1,148.21
Standard deviation	7.92	6.80	2,516.87	1,615.53
25th percentile	5.00	4.00	120.00	178.11
50th percentile	11.00	8.00	300.00	474.38
75th percentile	17.00	13.50	750.00	1,548.82

Panel C: Country count (ctry_count) is obtained by determining the number of geographical locations that the PE fund invest into based on the overall sample of PE funds in the study.
Panel D: Top quartile variable is Obtained by allocating a dummy variable to quartile 1 fund performance according to the quartile 1 classification by Preqin.

	Panel C- Independent variable: Ctry_Count		Panel D- Independent variable: Topquartile	
Descriptive statistic	Single Geographic PE Fund	Multi-Geographic PE Fund	Single Geographic PE Fund	Multi-Geographic PE Fund
N (observations)	7,750	592	7,750	592
Mean	1.00	6.27	0.24	0.28
Standard deviation	-	3.08	0.43	0.45
25th percentile	1.00	4.00	-	-
50th percentile	1.00	6.00	-	-
75th percentile	1.00	7.00	-	1.00

Summary Descriptive Statistics- Dependent Variable

This table reports summary descriptive statistics of the performance returns of single geographic PE fund compared to multi geographic or regional PE funds. The PE funds have vintage years starting from 1973 to 2018 and is obtained from Preqin's private equity database.

Panel E: Only PE funds are studied in the sample and the multiple 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 E- Dependent variable: Multiple (TVPI)	
Descriptive statistic	Single Geographic PE Fund	Multi-Geographic PE Fund
N (observations)	7,557	576
Mean	1.67	1.60
Standard deviation	1.28	0.75
25th percentile	1.19	1.17
50th percentile	1.50	1.44
75th percentile	1.87	1.85

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 F- Dependent variable: DPI (Distributions over paid in)	
Descriptive statistic	**Single Geographic PE Fund**	**Multi-Geographic PE Fund**
N (observations)	7,628	582
Mean	111.67	100.90
Standard deviation	112.96	99.65
25th percentile	23.28	13.46
50th percentile	105.20	82.00
75th percentile	159.96	152.54

Panel G: Only PE funds are studied in the sample and the Net IRR used for the performance measurement by Preqin has taken into consideration both the management fees and the performance fee or carried interest charged by the GPs to the LPs.

	Panel G- Dependent Variable (Net IRR)	
Descriptive statistic	**Single Geographic PE Fund**	**Multi-Geographic PE Fund**
N (observations)	6,305	464
Mean	16.19	16.10
Standard deviation	32.82	14.84
25th percentile	7.67	7.29
50th percentile	13.00	13.12
75th percentile	20.20	20.00

Panel H

Summary Descriptive Statistics

This table reports 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 starting from 1973 to 2018 and is obtained from Preqin's private equity database. The summary statistics is based on the full sample of PE funds pursuing these 3 strategies and the performance metric used is the multiple (Total Value over paid in). The year of assessment for the PE funds performance is taken in 2019.

		Performance metric: Multiple (TVPI)	
Descriptive statistic	**Buyout funds**	**Growth or Pre-IPO**	**Fund of Funds**
N (observations)	4,225	994	2,354
Mean	1.73	1.62	1.56
Standard deviation	1.08	1.12	0.60
25th percentile	1.17	1.03	1.23
50th percentile	1.56	1.40	1.48
75th percentile	2.06	1.90	1.74

Panel I

Summary Descriptive Statistics

This table reports 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 starting from 1973 to 2018 and is obtained from Preqin's private equity database. The summary statistics is based on the full sample of PE funds pursuing these 3 strategies and the performance metric used is the DPI (Distributions over paid in). The year of assessment for the PE funds performance is taken in 2019.

	Performance metric: DPI		
Descriptive statistic	**Buyout funds**	**Growth or Pre-IPO**	**Fund of Funds**
N (observations)	4,263	1,004	2,386
Mean	130.64	91.63	90.08
Standard deviation	127.26	122.10	79.34
25th percentile	36.32	3.65	19.83
50th percentile	123.80	50.00	90.46
75th percentile	188.20	144.21	135.00

Panel J

Summary Descriptive Statistics

This table reports 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 starting from 1973 to 2018 and is obtained from Preqin's private equity database. The summary statistics is based on the full sample of PE funds pursuing these 3 strategies and the performance metric used is the Net IRR which has been calculated net of all GP fees. The year of assessment for the PE funds performance is taken in 2019.

	Performance metric: Net IRR		
Descriptive statistic	**Buyout funds**	**Growth or Pre-IPO**	**Fund of Funds**
N (observations)	3,574	736	2,001
Mean	16.50	15.76	11.65
Standard deviation	19.52	22.80	8.51
25th percentile	8.00	7.42	7.06
50th percentile	14.10	12.98	10.70
75th percentile	22.91	20.77	15.01

Panel K

Summary Descriptive Statistics

This table shows the performance of single geographic buyout funds versus multi geographic buyout funds. Fund vintages are taken from 1973 to 2018 and the assessment year used for return calculations is 2019. Single geographic funds refer to funds investing in a single geographical location while multi geographic funds refer to funds investing in 3 or more geographic locations. Performance metrics used are the multiple and the DPI (Distributions over paid in).

Buyout Fund Strategy	**Multiple (TVPI)**		**DPI**	
Descriptive statistic	**Single Geographic**	**Multi Geographic**	**Single Geographic**	**Multi Geographic**
N (observations)	3,309	342	3,339	344
Mean	1.73	1.62	131.73	111.46
Standard deviation	1.13	0.77	131.33	104.67
25th percentile	1.15	1.17	38.70	14.58
50th percentile	1.56	1.47	122.92	108.00
75th percentile	2.07	1.98	189.00	170.40

Panel L

Summary Descriptive Statistics

This table shows the performance of single geographic growth funds versus multi geographic growth funds. Fund vintages are taken from 1973 to 2018 and the assessment year used for return calculations is 2019. Single geographic funds refer to funds investing in a single geographical location while multi geographic funds refer to funds investing in 3 or more geographic locations. Performance metrics used are the multiple and the DPI (Distributions over paid in).

Growth funds strategy	**Multiple (TVPI)**		**DPI**	
Descriptive statistic	**Single Geographic**	**Multi Geographic**	**Single Geographic**	**Multi Geographic**
N (observations)	780	80	786	82
Mean	1.60	1.51	91.21	71.39
Standard deviation	1.08	0.89	120.24	103.28
25th percentile	1.04	1.00	2.46	4.33
50th percentile	1.41	1.35	51.04	44.11
75th percentile	1.90	1.70	146.47	85.80

Panel M

Summary Descriptive Statistics

This table shows the performance of single geographic fund of funds versus multi geographic fund of funds. Fund vintages are taken from 1973 to 2018 and the assessment year used for return calculations is 2019. Single geographic funds refer to funds investing in a single geographical location while multi geographic funds refer to funds investing in 3 or more geographic locations. Performance metrics used are the multiple and the DPI (Distributions over paid in).

Fund of funds strategy	**Multiple (TVPI)**		**DPI**	
Descriptive statistic	**Single Geographic**	**Multi Geographic**	**Single Geographic**	**Multi Geographic**
N (observations)	2,134	96	2,162	96
Mean	1.56	1.60	91.84	77.05
Standard deviation	0.61	0.50	80.71	61.89
25th percentile	1.23	1.32	20.30	23.20
50th percentile	1.48	1.49	94.18	78.36
75th percentile	1.74	1.68	136.32	123.45

Table 2: Fund performance using DPI as dependent variable					[95% Confidence interval]	
PE Fund Group	Observation	Mean	Std. Error	Std. Dev.		
Single Geographic (0)	7,628	111.6668	1.293368	112.9607	109.1314	114.2021
Multi Geographic (1)	582	100.8964	4.13048	99.6465	92.7839	109.0089
Diff [Mean(0) - Mean(1)]		10.7704	4.81924		1.323109	20.21769
Student's t statistics	t = 2.2348					
Degrees of freedom	8208					

Table 3A

Multivariate regression on the impact of geographical diversification on private equity (PE) returns with specific independent variables and controls

This table reports coefficient estimates from multivariate regressions on global private equity (PE) fund returns which are impacted by geographical diversification on the funds' investment returns. The dependent variables are net IRR, Multiple or TVPI (Total value over paid in capital) and DPI (distributions over paid in) which are provided on a voluntary basis from to Preqin. Natural log functions provided for multiple and DPI. The main independent variable of interest is the Ctry_count variable which determines the number of countries that the PE funds are currently investing into. Other independent variables include fund sizes in USD mn, fund age in years and top quartile classification. DiverseIndust variable is provided to determine if a pe fund is investing in diversified or concentrated industries. Controls are provided for strategy and years fixed effects. In addition a region variable to classify whether the PE funds are investing in mature markets like Europe, North America and Australasia or non mature markets like South America, Central America, Africa and Asia. Sample period includes funds with vintage years ranging from 1971 to 2018. The t-statistics, derived from robust standard errors clustered by fund are in parenthesis. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent Variables being studied		
Independent variables	**Net IRR**	**Log Multiple (TVPI)**	**Log (DPI)**
Ctry_count	-0.0163	-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**	0.0215**
	(3.40)	(7.83)	(10.81)
Top quartile	18.212**	0.30**	0.694**
	(27.45)	(56.33)	(32.86)
diverseIndust	-0.314	0.019**	0.177**
	(-0.38)	(3.37)	(6.49)
region	0.690	0.0219**	.0.166**
	(1.01)	(2.81)	(4.45)
Strategy Fixed Effects	Yes	Yes	Yes
Years Fixed Effects	Yes	Yes	Yes
R-squared	0.181	0.4745	0.742
N	7,154	8,479	8,563

Table 3B: Multivariate regression on the impact of geographical diversification on private equity (PE) returns with specific independent variables and controls

This table reports coefficient estimates from multivariate regressions on global private equity (PE) fund returns which are impacted by geographical diversification on the funds' investment returns. The dependent variables are net IRR, Multiple or TVPI (Total value over paid in capital) and DPI (distributions over paid in) which are provided on a voluntary basis from to Preqin. Natural log functions provided for multiple and DPI. The main independent variable of interest is the Ctry_count variable which determines the number of countries that the PE funds are currently investing into. Other independent variables include fund sizes in USD mn, fund age in years and top quartile classification. Interaction variable is provided for fund age and ctry_count variable (fundage x ctrycount) to ascertain the joint effect of geographical diversification with fund age. diverseIndust variable is provided to determine if a PE fund is investing in diversified or concentrated industries and an interaction variable of diverseIndust and ctry_count (diverseIndust x ctrycount) is used to observe the joint effects of industry and geographical diversification. Controls are provided for strategy and years fixed effects. In addition a region variable to classify whether the PE funds are investing in mature markets like Europe, North America and Australasia or non mature markets like South America, Central America, Africa and Asia. Sample period includes funds with vintage years ranging from 1971 to 2018. The t-statistics, derived from robust standard errors clustered by fund are in parenthesis. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent Variables being studied		
Independent variables	**Net IRR**	**Log Multiple (TVPI)**	**Log (DPI)**
Ctry_count	-0.981**	-0.012**	-0.062**
	(-2.92)	(-4.78)	(-2.68)
Log (fund_size)	-0.904**	-0.01**	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)
diverseIndust	-0.501	0.007	0.13**
	(-0.43)	(1.01)	(3.16)
Fundage x Ctrycount	0.0830**	0.0002	0.001
	(3.01)	(0.97)	(0.89)
diverseIndust x Ctrycount	0.174	0.008**	0.032
	(0.45)	(2.63)	(1.43)
region	0.784	0.023**	0.17**
	(1.14)	(2.92)	(4.58)
Strategy Fixed Effects	Yes	Yes	Yes
Years Fixed Effects	Yes	Yes	Yes
R-squared	0.182	0.4751	0.742
N	7,154	8,479	8,563

Table 3C: Multivariate regression on the impact of geographical diversification incorporating a quadratic function

This table reports coefficient estimates from multivariate regressions on global private equity (PE) fund returns which are impacted by geographical diversification on the funds' investment returns. Dependent variables are net IRR, Multiple or TVPI (Total value over paid in capital) and DPI (distributions over paid in) which are provided on a voluntary basis from to Preqin. Dependent variables for Multiple and DPI are provided with a natural log treatment. The main independent variable of interest is the Ctry_count variable which determines the number of countries that the PE funds are currently investing into. The model also includes a quadratic function of ctry_count called ctry_count2. Other independent variables include fund sizes in USD mn, fund age in years and top quartile classification. DiverseIndust variable is provided to determine if a PE fund is investing in diversified or concentrated industries. Controls are provided using strategy and years fixed effects. In addition a region variable to classify whether the PE funds are investing in mature markets like Europe, North America and Australasia or non mature markets like South America, Central America, Africa and Asia. Sample period includes funds with vintage years ranging from 1971 to 2018. The t-statistics, derived from robust standard errors clustered by fund are in parenthesis. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent Variables being studied		
Independent variables	**Net IRR**	**Log Multiple (TVPI)**	**Log DPI**
Ctry_count	0.367	0.004	0.034**
	(1.48)	(1.43)	(2.56)
Ctry_count2	-0.033*	-0.001**	-0.005**
	(-2.07)	(-3.82)	(-5.44)
Log (fund_size)	-0.921**	-0.01**	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)
diverseIndust	-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

Table 4

2 SLS Regresson: First stage regressions

				No. of Obs	8,000	
				F(48, 7951)	17.8	
				Prob>F	0.0000	
				R-squared	0.097	
				Adj R-squared	0.0916	
				Root MSE	1.3791	
ctry_count	Coef.	Std. Err.	t	P>Itl	[95% conf. interval]	
lnfundsize	0.0662157	0.0125049	5.3	0.000	0.0417027	0.0907286
fund_age	-0.0783618	0.0287495	-2.73	0.006	-0.1347182	-0.022052
topquartile	0.0425832	0.0362893	1.17	0.241	-0.0285533	0.1137196
diverseIndust	-0.033331	0.0387552	-0.86	0.390	-0.1093014	0.0426393
region	-0.479715	0.053399	-8.98	0.000	-0.5843909	-0.375039
lnhost_cappctGDP	-0.2113081	0.0095136	-21.07	0.000	-0.2309663	-0.19165
constant	7.011356	0.2859332	17.45	0.000	6.223815	7.798897

Instrumental variables (2SLS) regression: 2nd stage

					No. of Obs	8,000
					Wald chi2(48)	22,469.42
					Prob > chi12	0.0000
					R-squared	0.7371
					Root MSE	0.87601
Log (DPI)	Coef.	Std. Err.	z	P>Izl	[95% conf. interval]	
ctry_count	-0.0863629	0.0301459	-2.86	0.004	-0.1454479	-0.027278
lnfundsize	0.032031	0.0079926	4.01	0.000	0.0163657	0.0476963
fund_age	0.2199504	0.181987	12.09	0.000	0.1842817	0.2556191
topquartile	0.7037286	0.0231045	30.46	0.000	0.6584446	0.7490126
diverseIndust	0.1821908	0.0245029	7.44	0.000	0.134166	0.2302155
region	0.1325902	0.039974	3.32	0.001	0.0542525	0.2109379
constant	-0.1002051	0.1865937	-0.54	0.591	-0.4659219	0.2655118

Table 5

First-stage regression summary statistics

Variable	R square	Adjusted R square	Partial R square	F(1,7951)	Prob > F
ctry_count	0.097	0.0916	0.0529	443.991	0.0000

Minimum eigenvalue statstics = 443.991

Robust testing: 2SLS Relative Bias table

	5%	10%	20%	30%
2SLS Relative Bias		(not available)		
	10%	15%	20%	25%
2SLS Size of nominal 5%	16.38	8.96	6.66	5.53
LIML Size of nominal 5%	16.38	8.96	6.66	5.53

Table 6

OLS and 2SLS multivariate regression model estimates and model results

This table reports OLS and 2 SLS (2nd stage) coefficient estimates for global private equity (PE) fund returns which are impacted by geographical diversification on the funds' investment returns. The dependent variables for comparison are are the DPI and multiple (TVPI) which are provided on a voluntary basis from Preqin. Natural log functions provided for the dependent variables. The main independent variable of interest is the Ctry_count variable which determines the number of countries that the PE funds are currently investing into. Other independent variables include fund sizes in USD mn, fund age in years and top quartile classification. Interaction variable is provided for fund age and ctry_count variable (fundage x ctrycount) to ascertain the joint effect of geographical diversification with fund age. diverseIndust variable is provided to determine if a PE fund is investing in diversified or concentrated industries. Controls are provided for strategy and years fixed effects. In addition a region variable to classify whether the PE funds are investing in mature markets like Europe, North America and Australasia or non mature markets like South America, Central America, Africa and Asia. Sample period includes funds with vintage years ranging from 1971 to 2018. The t-statistics (OLS and first stage models) and z-statistics (2 SLS models) derived from robust standard errors clustered by fund are in parenthesis. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variables being studied in the models					
	OLS regression estimates		First Stage		2 SLS regression estimates	
Independent variables	**Log (DPI)**	**Log (Multiple -TVPI)**	**Log (DPI)**	**Log (Multiple-TVPI)**	**Log (DPI)**	**Log (Multiple-TVPI)**
Ctry_count	-0.029**	-0.004**			-0.086**	-0.0195**
	(-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	0.0215**	0.027**	-0.078**	-0.075*	0.22**	0.026**
	(10.81)	(7.83)	(-2.73)	(-2.57)	(12.09)	(6.35)
Top quartile	0.694**	0.30**	0.0426	0.039	0.704**	0.302**
	(32.86)	(56.33)	(1.17)	1.08	(30.46)	(59.29)
diverseIndust	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**	0.0219**	-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

Table 7: Multivariate regression on the impact of geographical diversification on private equity (PE) returns using Public Market Equivalent (PME)

This table reports coefficient estimates from multivariate regressions on global private equity (PE) fund returns which are impacted by geographical diversification on the funds' investment returns. The dependent variables are PME (public market equivalent) provided on a voluntary basis from to Preqin. PME is of prime interest as the PE performance metric with risk adjustments applied. Natural logarithmic treatments are applied to PME after a histogram chart analysis. The main independent variable of interest is the Ctry_count variable which determines the number of countries that the PE funds are currently investing into. Other independent variables include fund sizes in USD mn, fund age in years and top quartile classification. DiverseIndust variable is provided to determine if a pe fund is investing in diversified or concentrated industries. Invest_staff variable is the number of investment staff at the PE firm level. An Interaction variable of investstaff and ctry_count will evaluate effects of additional investment staff on geographical diversification Controls are provided using strategy and years fixed effects. Sample period includes funds with vintage years which covers the period of 2003 to 2018 due to availability of PME data in Preqin's database. T-statistics, derived from robust standard errors clustered by fund are in parenthesis. * Significant at the 5% level; ** Significant at the 1% level.

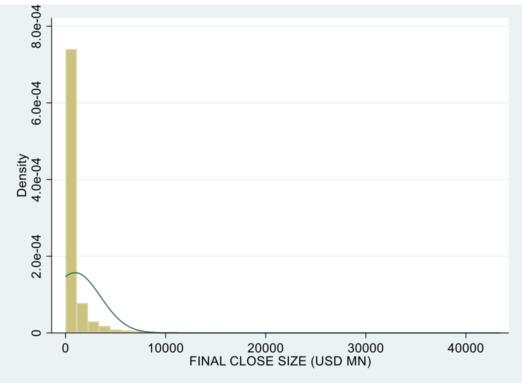
Independent variables	**Dependent Variable** **Log (PME)**
Ctry_count	-0.066
	(-1.90)
Log (fund_size)	0.003
	0.74
Fund_age	-0.014
	(-1.48)
Topquartile	0.001
	(0.13)
invest_staff	-0.003
	(-1.86)
diverseIndust	0.01
	(0.74)
Invest_staff x ctry_count	0.02
	(1.80)
region	0.01
	(0.55)
Strategy Fixed Effects	Yes
Years Fixed Effects	Yes
R-squared	0.032
N	1576

Table 8: Summary of Industry Feedback from PE funds and intermediaries

PE fund name	Contact role	AUM (USD $)	Industries Invested	Strategy Focus	Geographical Focus	Industry Feedback
Altair Capital (Polaris Capital Group)	Partner	$1.14B	Consumer, Education, Healthcare, Manufacturing, Services,	Buyout/LBO , Divestiture, Expansion / Late Stage, Growth	Southeast Asia	Have seen the diseconomy of scale issue in the past with smaller PE funds outperforming larger PE funds but this is due to smaller PE funds taking on additional risks. Study findings are useful as this is a topic that the PE industry has been interested in for a long time.
Castlelake	Director	$19B	Commercial services, Energy, Financial Services, Real estate, Transportation, Utilities	Co-Investment, Complex Situation, Distressed Debt, Reorganisation, Restructuring, Special Situations	Asia/Pacific, Europe, United States, Canada	Should consider if foreign exchange risks will play a role in the difference in performance between single geographic and multi geogrphic PE funds. Good to note that there is a mechanism to control for the difference between emerging and developed markets in the study.
China Investment Capital	Director	$1.05Tn	Communications, Consumer Services, Energy, Financial Services, Healthcare, Industrial, Media, Real Estate	Buyout, Distressed Debt, Seed Round, Early Stage, Expansion / Late Stage, Growth, Mezzanine Financing	Asia/Pacific, Europe, United States, Canada	Interesting theory as our funds prefer to invest in locations that we are familiar with rather than venturing into geographical areas with limited prior experience. The graphical diagram showing PE funds experiencing downward trajectory in returns after extensive geographical diversification is useful.
Family office fund	Senior Director	$100M	Facilities mgt software, clean tech, utilities	Later Stage VC, Growth equity	Singapore and Malaysia	Did not respond
KV Asia Capital	Associate Director	$363M	Financial services, Healthcare, Infrastructure services, Manufacturing, Resource related services	Balanced, Buyout, Seed Round, Early Stage, Growth	Southeast Asia	Findings make sense especially for the smaller PE funds that lack resources. It is good to see that the model has incorporated control variables like fund size and fund age which we think are important variables. We have seen some failure rates in single country PE funds before so the risk element is high.
Mizuho Asia Partners	CEO	$200M	Consumer Discretionary, Consumer Staples	Buyout, Growth, Mezzanine, PIPE, Special Situations, Turnaround	Asia/Pacific	Did not respond
Navis Capital Partners	Investment Director	$5B	Consumer Discretionary, Healthcare, Industrials, Information Technology	Buyout, Growth, Recapitalisation, Restructuring	Southeast Asia, Australia, Hong Kong	Useful analysis as it shows single country PE fund outperforming multi country or regional PE funds. Has the analysis taken into consideration differences in risk? Graphical diagram showing multi geographic PE funds experiencing downward trajectory in returns is useful for investment and planning strategy.
AMP Capital	Deal origination	$190B	Commercial Transportation, Communications and networking, Energy equipment and services, software, utilities and healthcare	Buyout, LBO, Turnaround, PE Growth, Secondaries, Distressed Debt, Special Situations, Venture	Asia Pacific, Australia, Europe	Have not seen a study like this before from personal experience but should think that a similar study has already been done. Findings should be useful for PE funds lacking in resources that are not able to pursue geographical diversification but have to adopt a focus investment strategy.
Risa Corporate Solution Fund	Partner	$655M	Consumer Discretionary, Communication Services, Financials, Healthcare	Buyout, Divestiture, Growth, Management Buyout, Restructuring, Mezzanine Financing	Asia/Pacific	Interesting approach to PE research and have not seen similar research findings previously. Consistent with our approach in avoiding multiple locations due to higher risks pose by some countries when the fund pursue global diversification. Appeciate the rigorous statistical analysis used to develop the study.
UOB Venture Management	Vice President	$1.32B	Consumer Goods, Energy, Healthcare, Information Technology	Buyout/LBO, Early Stage, Expansion / Late Stage, Privatisation	Asia/Pacific, United States	The hypotheses put forward and findings were very clear and useful. Interesting to find out more about industry diversification being able to help PE funds cope with the effects of geographical diversification.
Private equity intermediary (M&A Deal Advisory)	Advisor	N.A.	N.A.	N.A.	Southeast Asia	Portfolio diversification has been widely researched especially relating to public market investment. This piece of work brings a new perspective to private equity investment strategies particularly in South East Asia given the diversity of the region.

Note: N.A. Not Applicable
Source: Fund data from Pitchbook and Preqin

Figure 1: Fund size variable distributions with and without natural log treatments



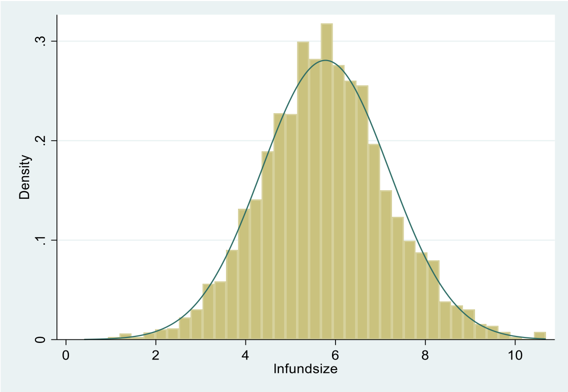
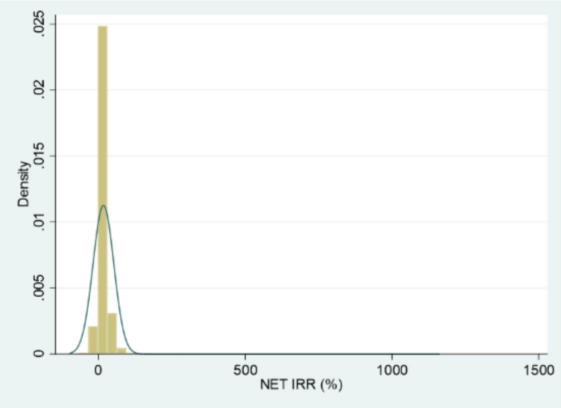


Figure 2: Net IRR variable distributions with and without natural log treatments



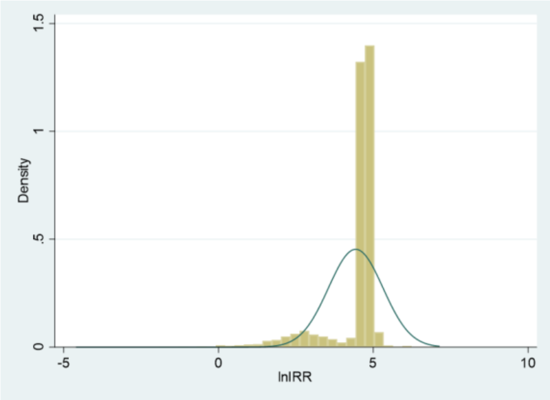
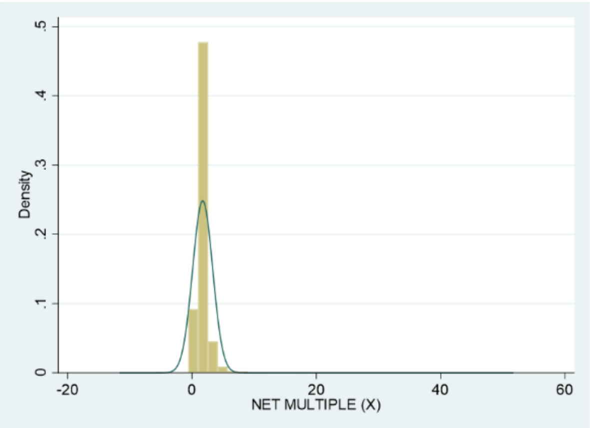


Figure 3: Multiple variable distributions with and without natural log treatments



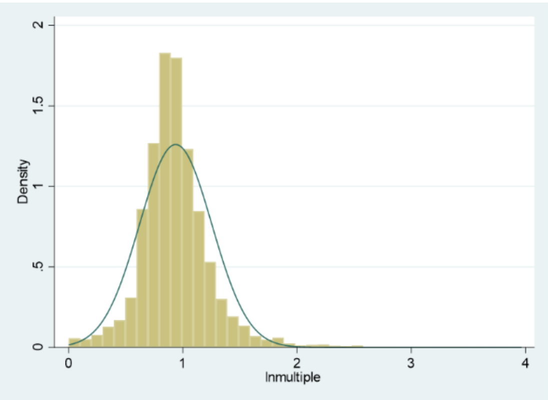


Figure 4: DPI variable distributions with and without natural log treatments

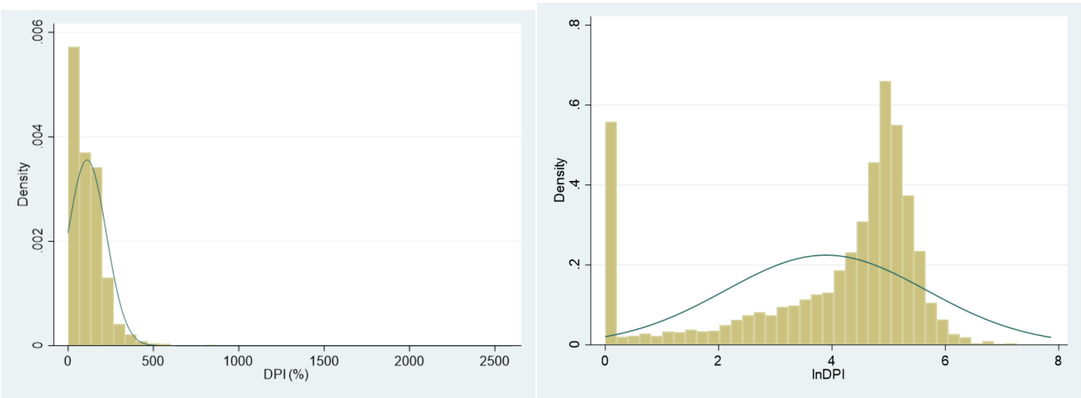


Figure 5: Bin scatter and line fit charts showing the relationship between dependent variables and geographical diversification (ctry_count)

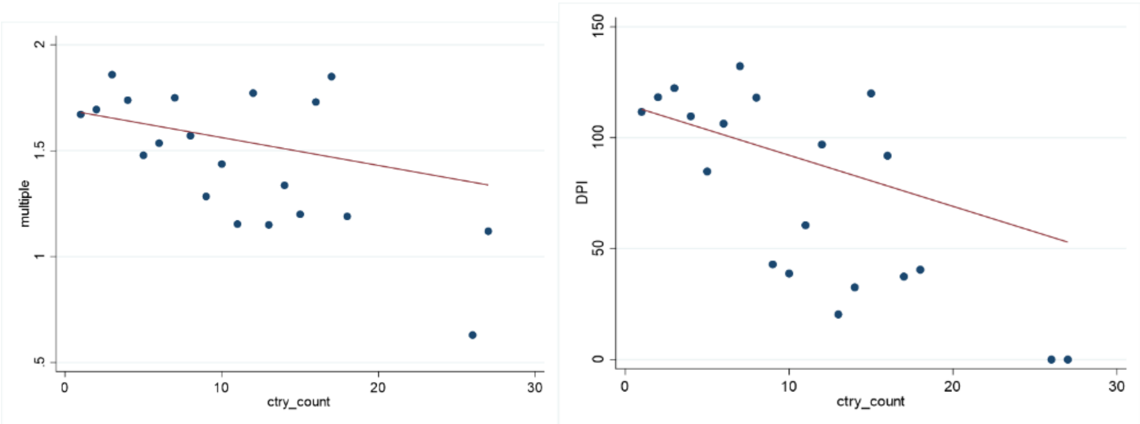


Figure 6: Host stock market capitalization as percent of GDP without and with natural log treatment

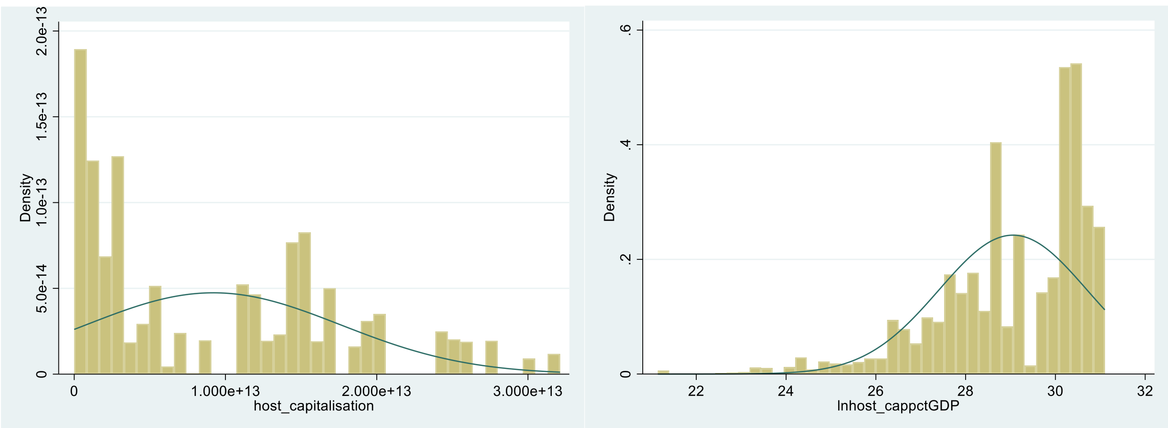


Figure 7: PME dependent variable distributions with and without natural log treatments

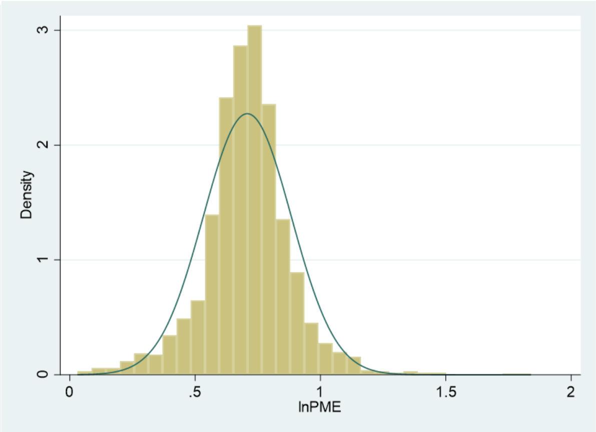


Exhibit 1
Correlation matrix

Model variables	ctry_count	Log (fund size)	fund age	top quartile	diverse_indust	Net IRR	Log (DPI)	Log (multiple)
Ctry_count	1.000							
log (fund size)	0.069	1.000						
fund age	-0.065	-0.181	1.000					
top quartile	0.025	-0.046	0.0003	1.000				
diverse_indust	0.019	0.040	-0.016	-0.038	1.000			
Net IRR	0.004	-0.081	0.039	0.340	-0.046	1.000		
Log (DPI)	-0.0365	-0.079	0.614	0.205	0.062	0.209	1.000	
Log (multiple)	-0.0031	-0.160	0.315	0.581	-0.016	0.501	0.546	1.000

Exhibit 2: Endogeneity Test		
Durbin (score) chi2(1)	3.30424	(p=0.0691)
Wu-Hausman F(1,7994)	3.28494	(p=0.0700)

Exhibit 3
Satisfying Exclusion Restriction Condition: Regression of lnhoststockmkt_retrn against lnDPI

No. of Obs	9,130
F(1, 9128)	0.07
Prob > F	0.7958
R-squared	0.0000
Root MSE	1.7779

lnDPI	Coef.	Robust Std. Err.	t	P>ltl	[95% conf. interval]	
lnhoststockmkt_retrn	0.006093	0.0235452	0.26	0.796	-0.040061	0.0522469
constant	3.864649	0.1177643	32.82	0.000	3.633804	4.095493

Case Study of Navis Capital Partners

Navis Capital Partners is one of the largest Asian private equity firm established in 1998 and based in Kuala Lumpur, Malaysia with more than USD 5 billion assets under management. The firm specialises in buyouts, recapitalizations and financial restructurings, predominantly in Southeast Asia, Australia, and Hong Kong. Navis' investments include food processing, fast food and casual dining, industrial products, fast moving consumer goods, advertising, auto rentals, and professional services.

Navis is not reliant on leverage to drive returns. They target companies with an investment size of USD $50m to $150m while acquiring a majority stake in its portfolio companies and makes control investments. Navis contributes capital and management expertise to its portfolio companies with the objective of achieving value creation in firms through growth, margin improvements and asset efficiency enhancement.

Exhibit A highlights some of Navis' transactions since its establishment. Navis during the early fund vintages post establishment focus mainly on a few select geographical locations like Malaysia, Singapore and Thailand. As Navis started to raise larger funds in recent vintages, the firm pursued extensive geographical diversification into locations which includes New Zealand, United Kingdom, Vietnam, Australia, Morocco and Germany.

Exhibit B shows Navis's fund performance from 1999 to 2013 based on Net IRR and multiple. Although Navis has been successful in raising larger fund sizes due to its brand recognition and resources, performance has been moribund compared to the early years. The Net IRR figures of its fund vintages from 2009 onwards are mostly below the mean IRR of 16.10% for multi geographic PE funds and mean IRR of 16.19% for single geographic PE funds shown in the summary descriptive statistics of the study. A possible explanation can be an overpayment issue potentially due to limited attention issue.

Exhibit A: Navis capital private equity transactions

Company Name	Deal Date	Industry	Geography	Deal Type	Deal Size (USD)
Bangkok Ranch	1-Jan-99	Food Products	Thailand	Buyout/LBO	-
Cemex	24-Jan-00	Raw Materials	Mexico	PIPE	$106.00M
Drypers Malaysia	1-Feb-01	Personal Products	Malaysia	Buyout/LBO	-
Mentor Media	1-Jan-06	Logistics	Singapore	Buyout/LBO	$103.00M
King's Safetywear	24-Dec-08	Footwear	Singapore	Buyout/LBO	$65.08M
Eng Kong Holdings	4-Jun-10	Logistics	Singapore	Buyout/LBO	$55.50M
Adampak	18-Jun-12	Commercial Products	Singapore	Buyout/LBO	$86.52M
Brickfields Asia College	12-Sep-13	Education	Malaysia	PE Growth/ Expansion	$21.43M
Tri-Star Industries	8-Jul-14	Industries Supplies and Parts	Singapore	Buyout/LBO	$60.05M
Texon International Group	5-Apr-16	Textiles	United Kingdom	Buyout/LBO	142.78M
Mainland Poultry	26-Apr-17	Animal Husbandry	New Zealand	Buyout/LBO	$244.74M
Saitex	21-May-18	Commercial Products	Vietnam	PE Growth/ Expansion	-
Device Technologies	1-Jan-19	Distributors/Wholsaler	Australia	Buyout/LBO	$500.18M
Networking Payment Systems	27-Nov-20	Electronic Equipment and Instruments	Morocco	Buyout/LBO	-
Hansecontrol Group	31-Dec-20	Commerical Services	Germany	Buyout/LBO	-

Source: Pitchbook

Exhibit B: Navis Capital Partners fund vintage performance

Fund Name	Vintage	Net Multiple	Net IRR
Navis Asia Fund I and II	1999	2.83	27.2
Navis Asia Fund III	2001	1.43	7.3
Navis Asia Fund NMF	2002	1.3	5.8
Navis Asia Fund IV	2004	1.47	7.7
Navis Asia Fund IV Shariah	2004	1.45	7.2
Navis Asia Fund V	2007	1.61	7.8
Navis Asia Fund V Shariah	2007	2.53	18.4
Navis Asia Fund VI	2009	1.18	2.7
Navis Asia Fund VI Shariah	2009	1.19	2.8
Navis Malaysia Growth Opportunities Fund I	2010	1.49	5
Navis Asia Fund VII	2013	1.56	13.9
Navis Asia Fund VII Shariah	2013	1.68	14.9

Source: Preqin

One example is Tri-Star Industries, an oil and gas component manufacturer. The buyout of Tri-Star Industries completed at around 15x EBITDA multiple is considered at the top end of market valuation during that period. Another transaction, Dunkin Brands had an even higher EBITDA multiple of 18x[6]. This is in comparison to the earlier deals such as King's safety wear, a landmark Navis deal, highly profitable and done at a reasonable valuation of 8.69x multiple[7]. Past studies have shown that larger PE funds have overpaid for transactions due to the limited attention issue and the main study findings allude to the adverse impact of geographical diversification on PE fund returns. Navis Capital with its latter fund vintages not performing as well compared to its first vintage and below the mean IRR performance of PE funds in the study sample is a case of how extensive geographical diversification and subsequently limited attention can adversely impact PE fund returns.

[6] Deal valuation data from Pitchbook
[7] Deal valuation data from Pitchbook

Case Study of Creador

Creador makes PE investments in growth orientated companies across South Asia and Southeast Asia with more than USD 1.5 bn assets under management. Creador is based in Kuala Lumpur, Malaysia and founded in 2011. The fund makes minority growth investments of USD 10 mn to 50 mn and will also invest in buyout and expansion or late stage venture deals. It uses operational expertise to accelerate growth in portfolio companies. Creador invests in financial, healthcare, life sciences, consumer and manufacturing sectors.

Landmark transactions include the acquisition of OldTown White Coffee, a Malaysian style cafe chain and coffee manufacturer. Creador completed the investment at USD 15 mn with deal Size/Ebitda multiple of 0.7x. Simba Indosnack Makmur, an Indonesian manufacturer of breakfast cereals was acquired one year later through a USD 35 mn leveraged buyout at 1.59x Deal Size/Revenue multiple considered a high valuation by industry standards. Ashiana Housing acquired at a PE ratio at 109.5x and later sold at 22.8x highlights the firm's challenges.

Company Name	Deal Date	Industry	Geography	Deal Type	Deal Size (USD)
PT BFI Finance Indonesia	19-May-11	Consumer Finance	Indonesia	PIPE	$169.00M
OldTown White Coffee	14-May-12	Beverages	Malaysia	PIPE	$15.00M
Simba Indosnack Makmur	25-Mar-13	Food Products	Indonesia	Buyout/LBO	$35.00M
Somany Ceramics	13-Jan-14	Building Products	India	PIPE	$8.06M
Vectus Industries	19-Jun-14	Commercial Products	India	PE Growth/ Expansion	$16.89M
Ashiana Housing	11-Feb-15	Building and Property	India	PIPE	$32.21M
RedCap Pharmacy	1-May-15	Healthcare	Malaysia	Buyout/LBO	$27.49M
City Union Bank	1-Mar-16	Regional Banks	India	PIPE	$19.07M
iValue InfoSolutions	21-May-19	Network Management Software	India	PE Growth/ Expansion	$18.00M
Kogta Financial	7-Oct-19	Consumer Finance	India	PE Growth/ Expansion	$42.08M

Source: Pitchbook

Fund Name	Vintage	Fund Size (USD)
Creador I	2011	$130M
Creador II	2013	$331M
Creador III	2015	$419M
Creador IV	2018	$580M
Creador V	2021	First Close: $500M

Source: Preqin

Creador similar to Navis started operations by investing in only a few selected geographical locations, mainly Malaysia, India and Indonesia with a preference for investing in Malaysia and Indonesia. After raising larger funds, Creador ventured into several countries as seen from its latest Creador V fund vintage that provides financing to companies in India, Malaysia, Philippines, Singapore, Vietnam, Sri Lanka, and Thailand. However, in contrast to Navis, Creador takes on a more controlled and calibrated approach to geographical diversification, staying close to its five core PE markets of Malaysia, India, Indonesia, Philippines and

Vietnam. Creador does not venture into locations outside of its core geographical areas, preferring to build expertise in its core markets.

Fund performance data is not available but information from public domain mentions the first vintage fund having a 25 percent IRR target and focussing mainly on Malaysia and Indonesia[8]. Creador's justification for expanding into multi geographic PE funds and not just single country funds emanates from the challenge of finding enough opportunities in a single country like Malaysia[9]. The fund prefers to be patient and works closely with its portfolio firms to drive performance as it views Southeast Asia as a region where PE firms have experienced poor performance and have high risk exposure due to the presence of a larger number of inferior companies in the region.

This strategy of controlled geographical expansion coupled with its patient value creation efforts with portfolio firms have been effective for Creador as seen by the success of PE deals in its more recent fund vintages. Creador exited from Somany Ceramics to a consortium of undisclosed institutional investors in 2017 at 77% IRR, 5.30x Exit Multiple, 1.42x Deal Size/EBITDA, 39.22x PE multiple[10], considered to be a highly successful PE transaction. In a recent Indian PE transaction, Creador acquired Corona Remedies in 2016 and exited from the investment in April 2021 at a 3.7x exit multiple or 32 percent IRR which showcased its ability to execute complex deals in a challenging market and yet exit profitably[11].

The success of its more recent transactions demonstrates Creador's strategy of staying close to its core markets and working with portfolio firms has been effective in creating value for its investors. This strategy of controlled geographical diversification is consistent with one of the main study findings of an inverted U shape relationship between geographical diversification and PE fund returns where excessive geographical diversification will have an adverse impact on returns after reaching an inflexion point. Analysis of Creador's III, IV and V vintage performance metrics data when available in the public domain will provide further justification and support for the success of Creador's controlled diversification strategy.

[8] Creador's second act by Media Partners Asia article 18 August 2013
[9] Deal street Asia article 21 August 2018 – Southeast Asia is filled with mediocre performance: Brahmal Vasudevan, Creador.
[10] Source Pitchbook
[11] https://creador.com/creador-exits-indian-pharma-player-to-chryscapital/