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Experience as a Performance Driver in Private Equity: An Empirical Analysis of Buyout and Venture Capital Funds

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ABSTRACT

This thesis analyses the impact of a Private Equity firm's experience on fund performance. It draws on a manually extended data set from Preqin, consisting of 413 liquidated Buyout and Venture Capital funds from North America and Europe with Vintage years between 1980 and 2012. We break down firm experience into multiple variables based on organisational learning theory. We find that experience can be a reliable performance predictor, depending on the variable employed. The most significant, positive, and robust predictor is a firm's age. We also find that a higher number of deals in a top-quartile fund negatively affects the returns of the succeeding fund, which might be driven by overconfidence. Further, a prior fund's industry heterogeneity has a positive significant but not robust effect on the subsequent fund's returns. This thesis adds to the academic literature through its dedicated focus on experience and the joint analysis of multiple existing and newly employed experience proxies within one model.

Keywords: *Private Equity, Buyouts, Venture Capital, Experience, Performance Measurement*

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List of Abbreviations

GP	General Partner
HHI	Herfindahl–Hirschman Index
IPO	Initial Public Offering
IRR	Internal Rate of Return
LP	Limited Partner
MOIC	Multiple of Invested Capital
PE	Private Equity
PME	Public Market Equivalent
VC	Venture Capital
VIF	Variance Inflation Factor

1 Introduction

The Private Equity (PE) industry experienced a decade of tremendous growth, mounting in a year of records in 2021. With more than four billion US Dollars, the global Buyout deal value of 2021 was approximately twice the size it had been in any of the last ten years. Fundraising for global Buyout capital has nearly tripled since 2011 and Venture Capital (VC) funds have grown even faster (MacArthur et al., 2022). This high influx of capital was presumably supported by the asset class's high average returns. Research has shown that the PE industry consistently outperforms public market benchmarks (Higson & Stucke, 2012; Harris et al., 2014; Phalippou, 2014; Ang et al., 2018). However, in 2022, concurrently with political aggressions and increasing inflation, deal volume and valuations started to sink (MacArthur & Rainey, 2022).

Given both the heated market and the signs of recession, predicting which funds will likely perform well would be even more valuable knowledge for investors. Korteweg & Sorensen (2017) found that first-quartile firms, on average, consistently outperform fourth-quartile firms by seven to eight percent annually. This consistent outperformance implies that some Private Equity fund managers are more skilled than others. Hence, skill might be a good predictor for future fund returns. Skill is a factor that can influence the fund's deals, market timing, and industry choice (Braun et al., 2017). However, assessing a PE firm's skills is difficult. A common variable to assess skill in research is prior performance. However, studies have shown that prior performance is noisy and can be a result of mere luck (Korteweg & Sorensen, 2017). Further, it is only partially available at the point of fundraising or based on performance from possibly many years back (see Harris et al., 2022). Therefore, it is difficult to identify good funds based on past performance and there is little investable persistence (Korteweg & Sorensen, 2017).

An alternative variable that can be used to estimate a fund manager's skill and future returns is a fund manager's experience. This is because experience is generally seen as a progenitor of skill (see, e.g., Sorensen, 2007). Further, experienced fund managers may have access to better deal conditions due to reputation (Hsu, 2004). In contrast to prior performance, experience is more readily available at the point of fundraising, making it a practicable variable. Despite the potential importance of experience as a fund performance predictor, little focused research has been dedicated to this topic. To address this research gap, this thesis focuses on PE firm experience as a predictor of fund performance.

Fundamentally, experience is gained by individuals when drawing conclusions from actions and their results. Within Private Equity, well-suited subjects of investigation would, therefore, be investment professionals and partners who execute and evaluate the deals. Due to the private nature of Private Equity, we do not have access to data on the individual level. We do, however, have access to firm-level data, which is generally more available for researchers as well as investors when making investment decisions. The effect of organisational experience on skill and performance is grounded in organisational learning theory. As organisations gain experience, they change their understanding based on past actions and accumulate organisational learning. The newly acquired learnings ultimately might lead to a change in behaviour and positively drive performance (Argote & Miron-Spektor, 2011; Castellaneta et al., 2022).

The limited existing literature that has investigated the impact of experience on fund returns in Private Equity has three main limitations. First, most existing studies focus on three variables only: firm age, fund sequence, and the number of prior deals. Thereby, other potential aspects that may influence experience and its impact on performance are disregarded. Second, the studies only look at one or two experience measures at a time which neglects the joint effect a variety of measures might have on performance. Third, the results of the studies are inconsistent (compare, e.g., Kaplan & Schoar, 2005; Aigner et al., 2008; Phalippou & Gottschalg, 2009; Sensoy et al., 2014).

In the wake of inconsistent results in the limited academic research and after studying organisational learning theory, we believe that it is important to capture many different dimensions of experience. To do so, we adapted a general learning framework from Lapré & Nembhard (2011) to ensure that we cover a sufficient depth and breadth of experience. The measures of experience we derived from the framework are time, cumulative amount, and heterogeneity. Time looks at how much time was spent reflecting on and learning from experiences. Cumulative amount looks at task repetition and is based on the idea that operations can be improved through each additional experience made. Heterogeneity looks at how diversified previous experiences were and whether you learn more from specialised or diversified experiences. To transfer this framework to the PE landscape, we mapped the measures with six PE experience proxy variables and examined their effect jointly in one study.

In terms of data, we employ the Preqin Private Capital database as of August 2022, including liquidated Venture Capital and Buyout funds with Vintage years from 1980 to 2012.

After a thorough filtering process and manual data addition from Preqin, we run a multiple linear regression model on a sample of 413 funds.

We find three significant results in our main model. First, we show that the age of a PE firm has a significant and positive effect on fund returns, highlighting the importance of time for reflection in order to enhance processes and investment decisions. Second, we find a significant and negative effect of a prior first-quartile fund's number of deals. A high number of good experiences in the prior fund might cause misleading confidence, reducing diligence. Third, we find a positive effect of prior industry investment diversification on future fund returns. Fund managers might learn less from specialised and more from diversified industry experience. However, the effect is not robust if we control for specialisation in the current fund. The discussed results are based on Multiple of Invested Capital (MOIC) as the performance metric. When switching the metric from MOIC to Internal Rate of Return (IRR), the results for most of our variables are losing significance. This inconsistency between performance metrics has also been found in previous studies (e.g., Aigner et al., 2008; Sensoy et al., 2014). It might be caused by the IRR's disposition to become substantially positive when capital is returned quickly, which strongly influences the variable's dispersion (see Kaplan & Sensoy, 2015; Braun et al., 2017, Doskeland & Strömberg, 2018).

Our thesis contributes to the current academic literature in three main ways. First, our study is unique in having a dedicated focus on experience and jointly analysing the interaction of multiple experience proxies in one study. Most previous studies only employed a single experience measure as a control variable. Second, we connect organisational learning theory with PE experience and employ two experience proxies that, to the best of our knowledge, have not been tested on fund returns. They encompass two lagged heterogeneity variables for geography and industry. Third, we use a more recent data sample than previous studies, which accounts for the potential change in the prediction power of experience proxies over time.

The remainder of this thesis is structured as follows. In Chapter 2, the related literature to Private Equity, performance, and General Partner experience is described. In Chapter 3, four hypotheses and two tests are developed. Chapter 4 introduces the database, data sample, variables, and methodology employed. In Chapter 5, the results of our regressions are discussed and tested for robustness. In Chapter 6, the conclusions from this thesis are drawn.

2 Related Literature

In this Chapter, we will introduce Private Equity as an asset class. Here, we focus on how PE firms operate, the performance of the asset class relative to public markets, and PE firms' prior experience as a performance driver. At the end of the Chapter, we also describe how our paper stands out from the existing literature and what contribution it makes.

2.1 Private Equity: Introduction and Performance

Private Equity, comprised of Buyout and Venture Capital, is part of the asset class Private Capital Markets. The PE industry is structured in limited partnerships, fund vehicles run by General Partners (GPs), which invest money on behalf of their investors (Limited Partners, LPs). The GPs invest the fund's money into companies that are either currently privately held or that are currently public and then taken private during the investment process. Most PE funds have a determined lifespan, with an industry standard of 10 years, with extension options. GPs usually raise new funds every few years, in accordance with their covenants, some faster than others. Operationally, the role of a GP encompasses a variety of tasks during a fund's life cycle. First, the GP has to generate deal flow, referring to the scouting of investment opportunities. Those opportunities the GP then evaluates on return potential and risks in a process called due diligence. Afterwards, a term sheet is negotiated and the GP invests in the company's equity. Then the GP monitors and assists the portfolio company during the so-called holding period. When the GP decides to sell its shares, it usually goes via initial private offering (IPO), trade sale, secondary sale, or liquidation of the company (see, e.g., Hellmann & Puri, 2002; Kaplan & Lerner, 2010; Doskeland & Strömberg, 2018).

When looking at the performance of PE as an asset class, average PE returns are usually compared against a public market benchmark (e.g., S&P 500). Although the magnitude varies between different papers and especially for VC funds, there is a general consensus that the PE asset class outperforms public markets in absolute terms (Higson & Stucke, 2012; Harris et al., 2014; Sensoy et al., 2014; Ang et al., 2018). Due to having an illiquidity and systematic risk premium, PE funds have to outperform the public market to be an attractive asset class (Doskeland & Strömberg, 2018).

While investments into an average PE fund might be profitable, this does not mean that all individual PE funds are beating public benchmarks. Not just choosing GPs at random is tremendously important because investment returns between individual PE firms vary considerably. For example, Korteweg & Sorensen (2017) saw a difference in top versus bottom-quartile firms of around seven to eight percent in returns per year. This should strongly compel LPs to look for predictors of good performance.[1] The next Section, 2.2, looks at the prior literature on one of those drivers, experience.

2.2 Experience as a Performance Driver in Private Equity

Both in the academic PE literature and in general organisational theory, experience has been discussed as one central driver of performance (e.g., Kaplan & Schoar, 2005; Argote & Miron-Spektor, 2011; Castellaneta et al., 2022). However, the literature with a dedicated focus on experience in PE is limited. In this Section, we first look at the literature about the qualitative impact of experience on a GP's operations. Subsequently, we outline the results of prior empirical research on the quantitative effect of experience on a GP's performance.

Sorensen (2007) identified two main channels through which experience may affect a GP's operations. The first channel of experience, called influence, details how experienced GPs add additional value to portfolio companies. First, GPs with more experience may be better at managing and monitoring their portfolio companies. They have worked for a longer time in PE governance and thus may be more skilled at driving a portfolio company's strategy. Second, more experienced investors generally have a larger network of managers, suppliers, and customers, which they can leverage for their portfolio companies. Third, experienced investors may have a higher outside reputation (see also Hsu, 2004). Through that, they may help a portfolio company to uncover unrealised or unrecognised value through higher visibility.

The second channel is called sorting and details how more experienced GPs have better deal access and signalling. More experienced GPs usually have a longer track record and thereby signal their skill of staying in business, which allows for positive interpretation from the market. This signalling effect may give these GPs access to proprietary and high-quality deal flow. Companies are looking not only for the highest valuation at investment, but also for a GP that can add tremendous value till exit (Sorensen, 2007; Schmidt et al., 2004).

[1] A wide range of Private Equity performance predictors have been analysed in previous studies. Valkama et al. (2013) provided an overview of papers that analysed certain performance drivers, which we extended. For example, analyses have been done on experience (e.g., Kaplan & Schoar, 2005; Phalippou & Gottschalg, 2009; Castellaneta et al., 2022), GP compensation (Metrick & Yasuda, 2010; Hochberg et al., 2014), specialisation (Knill, 2009; Le Nadant et al., 2018), financing type (Cumming, 2006), fund size (Higson & Stucke, 2012), syndication and network (Hochberg et al., 2007; Cumming, 2006), market returns and fundraising activity (Kaplan & Stein, 1993; Kaplan & Strömberg, 2009; Harris et al., 2014; Robinson & Sensoy, 2016). Other factors that have been analysed are leverage and deal amount (Valkama et al., 2013).

How much exactly each of these two channels impacts a GP's ability to create value is challenging to separate. One general problem of PE research is data availability. Often, the level of detail is limited, both for the individual investments as well as the organisational practices within a PE firm. At the deal level, studies that had access to very detailed data are often based on highly restrictive data sets (e.g., Lopez-de-Silanes et al., 2015; Braun et al., 2017). At the fund level, data availability is better because several platforms are providing data for industry professionals and academics.[2]

Despite the potential importance of GP experience as a return driver, little empirical research has been dedicated to this topic. However, GP experience has been a control variable in a number of studies. In the following paragraphs, the findings of these studies are presented, structured by the three most common experience proxies at the fund level: age of the PE firm, fund sequence, and the number of prior investments by the PE firm.

The first experience proxy used in prior research is the age of the PE firm. The general rationale for this proxy is that older GPs had more time to reflect on past experiences and to implement changes. Aigner et al. (2008) find that the experience of a GP measured in years has a significant and positive effect on fund returns.[3] In contrast, Schmidt et al. (2004) and Lopez-de-Silanes et al. (2015) did not find a significant effect of firm age on performance.

The second experience proxy, fund sequence, denotes the number of funds a particular GP has raised to date. GPs of funds with a higher sequence number have raised more funds and thus are generally assumed to be more experienced. However, there is no consensus in the existing literature on the predictive power of fund sequence for performance. On the one hand, Kaplan & Schoar (2005) find a significant and positive effect of fund sequence on returns.[4] On the other hand, Lopez-de-Silanes et al. (2015) find no significant effect of fund sequence.[5]

The third established proxy for experience in previous studies is the number of past investments of a PE firm. The results for this proxy are also inconsistent. On the one hand, Lopez-de-Silanes et al. (2015) conclude that the number of prior cumulative deals is not

[2] Harris et al. (2014) discuss four common data providers, including Preqin, Venture Economics, Cambridge Associates, and Burgiss.

[3] The positive effect of age on performance is confirmed by Hochberg et al. (2007), looking at investment exit rates. Further, Gompers (1996) finds a positive impact of GP age on IPO pricing.

[4] The significant results hold in the cross-section but not after adding firm-fixed effects. Lossen (2006) confirms the significant positive effect of fund sequence on returns. Sensoy et al. (2014) add that the effect seems to be stronger for Buyout funds and more recent time periods.

[5] Showing the ambivalent picture, Phalippou and Gottschalg (2009) find a positive relation between fund sequence and performance. However, their coefficient of fund sequence is not significant in many of their regression specifications, especially when controlling for past performance.

significantly correlated with deal returns. Braun et al. (2017), in contrast, state that the number of previous deals based on the fund family has a significant negative effect on performance, indicating that the performance of a GP decreases over its lifetime.

Our study differs from the existing papers described above in two main ways. First, we focus on more experience measures than any of the previous studies to cover a more comprehensive breadth and width of experience effects on fund performance. The studies described above are mostly limited to one experience measure. In terms of quantity, Lopes-de-Silanes et al. (2015) come closest, testing all three of the above proxies at a deal level. Yet, our study analyses experience at the fund level and adds two additional variables about experience specialisation that, to our best knowledge, have not been tested before.

Second, our study allows for a joint analysis of multiple experience proxies. By including all experience proxies in one model, we aim to observe the interaction of the individual, potentially diverging, effects of experience measures on fund performance. The outlined existing papers only included one experience measure as a control variable in their models. If they examined multiple measures (e.g., Lopes-de-Silanes et al., 2015), they swapped the measures for each other rather than including them all together. Two exceptions are Schmidt et al. (2004) and Aigner et al. (2008), who jointly tested sequence and age. Whereas the former found no experience proxy to be statistically significant, the latter finds only age to be significant.[6]

In addition to testing the existing experience proxies, we will introduce two new measures of experience based on prior industry and geographic investment specialisation. Hence, we will briefly introduce the existing PE literature that compares the effect of a specialised with a diversified investment approach. In contrast to the existing studies, our thesis looks at the experience effect of past and not current specialisation on a fund's performance, an analysis that, to the best of our knowledge, has not been done before. For example, Hochberg et al. (2015) outline that specialised GPs may hold sector-specific knowledge that provides a competitive advantage in investment selection and value creation. On the contrary, a diversified approach allows a GP to invest in a greater variety of sectors, some of which may have fewer bids and lower valuations due to reduced competition. The empirical results of the effect of specialisation on fund returns in past studies are inconsistent. Lossen (2006) found that industry diversification in investments has a positive impact on PE performance, while broader

[6] Aigner et al. (2008) find only age to be significant if using IRR as performance measure. If IRR is replaced by the Public Market Equivalent, both fund sequence and firm age are significant when included in the same model.

diversification in geography has no significant impact. Gompers et al. (2009), on the other hand, find a positive effect of specialisation on performance.

After studying the existing literature, we understood that experience might play an important role as a performance driver in PE across various dimensions. However, the empirical evidence of the effect of experience on performance is inconsistent for each variable and limited to a few experience measures. After reviewing and comparing previous studies, it is not obvious which experience measure can be used as a reliable predictor for PE performance, what magnitude various measures have, and how different experience measures interact with each other. Further, not all forms of experience are accurately measured or covered by the existing proxies. The diverging existing findings are likely the result of using a variety of PE data sets, model specifications, experience measures, and a wide range of different control variables. Hence, we conclude that the experience effect in PE is not well understood enough and demands further research.

3 Hypotheses Development

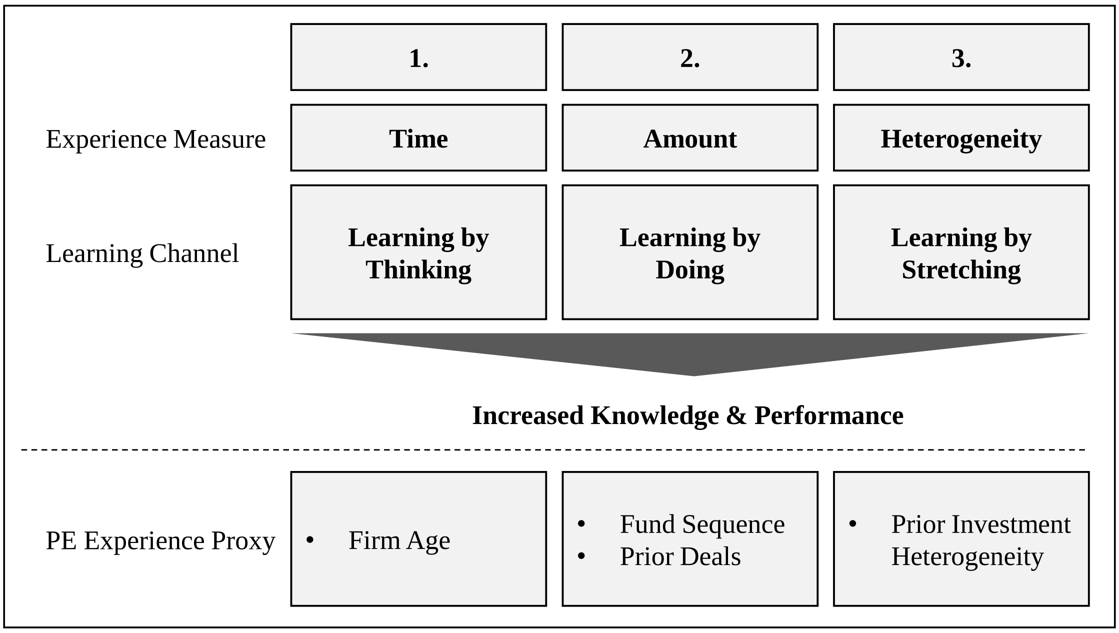
This thesis aims to investigate the effect of GP experience on fund returns. Thereby, it is important to determine how to define experience on an organisational level and measure its effect. The origin of experience at the organisational level is the individual. An individual gains experience by drawing conclusions from actions and their results. Within an organisation, the aggregation of individual experiences creates organisational experience. The underlying effect of organisational experience on skill and performance is grounded in research about organisational learning (Argote & Miron-Spektor, 2011). In this Chapter, we, therefore, develop our hypotheses based on organisational learning theory and test various PE experience measures and their impact on performance. At the end of this Chapter, Table 1 presents an overview of our hypotheses.

Organisational learning, at its core, is the development of organisational practices based on past experiences. As organisations gain experience, they change their understanding based on past actions and accumulate organisational learning. The newly acquired learnings ultimately might lead to a change in behaviour and positively drive performance (Argote & Miron-Spektor, 2011; Castellaneta et al., 2022). Although the role of experience as a source of organisational learning is well established in the literature, a growing number of researchers have started to question the fostering effect of experience. Not all types of experience are the same and not every experience is a reliable basis for performance improvement (Castellaneta et al., 2022; March, 2010). This finding was confirmed by the inconsistent results in our literature review across the existing PE experience proxies. Hence, we conclude that it is important to account for a sufficient level of detail and consider various measures when investigating experience and its effect on performance.

In the following part of this Chapter, we will develop four hypotheses and two tests that aim to analyse various experience effects on performance. To do so, we apply and extend a framework of organisational learning by Lapré & Nembhard (2011) (see Figure 1 below). The motivation for using the framework is to correctly assess both the existing and our newly developed PE experience proxies and to ensure that we cover a sufficient depth and breadth across the various dimensions of experience. The original framework uses the three experience measures time, amount, and maximum volume, to explain how industrial organisations learn from different experiences using different learning channels. Learning through all channels may increase organisational knowledge and performance. We slightly adjust the framework by replacing the experience measure maximum volume with experience heterogeneity which is better suited to the investment industry.

Figure 1: Learning Channels Linking Experience and Performance

Based on Lapré & Nembhard (2011), the figure below shows three different ways in which studies can link experience with performance improvement. The starting point is to distinguish between three ways in which experience can be measured: time, amount, and heterogeneity. Each measure has a distinctive learning channel through which the measure affects knowledge and performance: Learning by Thinking, Learning by Doing, and Learning by Stretching. At the bottom of the figure, various PE measures that are used in this study are assigned to the respective learning channels.



3.1 Learning by Thinking

The first experience proxy is time which acts through the learning channel *Learning by Thinking*. According to Lapré & Nembhard (2011), this channel is based on the assumption that individuals and organisations need time to reflect on experiences to learn from them. Thereby, it does not matter how many times an experience is made. Instead, the amount of elapsed time is important because passing time allows an organisation to learn and drive change.

Firm Age

Looking at PE firms, one measure that proxies this learning channel is the GP firm's age. The older a GP gets, the more time it had to reflect on its investment experience and thus refine and learn from past decisions. Although time is an established proxy for experience in organisational learning, the number of studies in PE that looked at this effect is scarce (see Chapter 2). Hence, we investigate the effect of age. Our first hypothesis is:

H 1: The more time has passed since the General Partner's first-time fund, the higher the current fund's performance.

3.2 Learning by Doing

The second concept of Lapré & Nembhard's (2011) framework is *Learning by Doing*, which refers to the cumulative number of times an experience is gained. The underlying idea is that through task repetition, operations can be refined through each additional experience made. Advocates of *Learning by Doing* claim that learning only takes place through the attempt to solve a problem. Thus, learning must necessarily be linked to activity (Arrow, 1962).

Fund Sequence

An intuitive measure to investigate the effect of *Learning by Doing* on fund performance is fund sequence. The more funds a GP has raised, the more often it has gone through the whole fund life cycle of fundraising, investing, value creation, and exiting. If *Learning by Doing* has a positive effect, a higher fund sequence should positively impact fund returns.

While fund sequence and firm age cover different dimensions, they correlate.[7] When fund sequence increases by one unit, the years of experience of the PE firm have increased too, unless the new fund was raised in the same year as the prior fund. However, while the two variables move in the same direction, they do so at different speeds. Within and across firms, the length of fundraising cycles can vary strongly. Hence, sequence and age are diverging over time. Further, conceptually, the age variable aims to capture the effect of experience based on reflection, whereas fund sequence is focused on task activity. Hence, both variables are distinct measures in the PE context and need to be included when looking for suitable experience predictors of fund returns. Following the idea of a positive effect of *Learning by Doing*, our second hypothesis is:

H 2.1: The more funds a GP has raised in the past, the higher the performance of its current fund.

Prior Deals

Apart from the high-level measure fund sequence, *Learning by Doing* can also be investigated on a more granular level. The returns of a fund are strongly driven by its underlying deals. Each

[7] We test for the pairwise correlation of our variables in Section 4.2.

additional investment generates experience, which touches on, for example, structuring deals, monitoring firms, and expanding the network (Hsu, 2004).

Unfortunately, we cannot draw the total number of a GP's former deals since the investment history of many GPs in our database is incomplete. However, we find a sufficient number of funds with deal data available for the directly preceding fund. Consequently, we use the number of deals of the prior fund as our experience proxy for the *Learning by Doing* channel's more granular analysis. The choice of only looking at the most recent fund can also be underpinned by existing learning literature which states that the recency of experience plays a decisive role. Tversky & Kahneman (1974) discuss this under the term recency bias, which shows that more recent experiences have a stronger impact on individual decisions than experiences made earlier in life. Argote & Epple (1990) connect the recency bias to the organisational learning theory and find considerable evidence of knowledge decay within organisations. We conclude for our analysis that a measurable effect of *Learning by Doing* could be driven by the number of deals done in the recent past. Hence our second hypothesis within the *Learning by Doing* dimension is:

H 2.2: The more deals a GPs has done in the prior fund, the more experience he gained, which positively drives fund performance of the current fund.

Success of Prior Deals

The analysis of the number of deals and thus the effect of the cumulative amount of experience on performance can be broken down further. Within the learning literature, there is a discussion about whether certain events can influence the experience gained more than others. In the case of investment experience, the distinction between success and failure is an interesting angle to look at. Evidence in research shows that firms react differently to the experience of failure and success. It was found that success triggers the actors to engage in local search that is limited to the scope of the previous actions, to repeat or enhance past success. Failure, on the other hand, requires looking outside of the previous environment and triggers an actor's search for new possibilities to correct and improve performance (e.g., March, 1991).

Following this research, it would be interesting to investigate the interaction between the prior number of deals and prior success. We expect each additional prior deal to have generated experience and increased skill. We further expect prior success to positively impact fund returns for two reasons. First, GPs with a prior successful fund have more best-practices they can rely on for future deals. Second, successful fund managers might be generally better at drafting learnings from past experiences, which put them into first-quartile in the first place. This would imply that successful firms might generate more learnings from more deals than not-successful firms would. Hence, given the two positive impacts, for the interaction between the two variables, we expect an even stronger effect on performance. Thus, our third hypothesis for the *Learning by Doing* dimension is:

H 2.3: The more deals a GP has done in a prior successful fund, the better the performance of the current fund.

3.3 Learning by Stretching

The third learning channel in the framework from Lapré & Nembhard (2011) is *Learning by Stretching*. Compared to the two previous channels which are looking at the time and amount dimension, this channel is dealing with the heterogeneity of prior experience. The underlying idea is that the learning effect of diversified experience is different from specialised experience. Schilling et al. (2003) emphasise that diverse experiences foster a more complex understanding of processes and train problem-solving abilities. Yet, more diverse experiences might be more difficult to integrate and utilise in future tasks. Specialisation, on the other hand, allows to focus on certain tasks which supports the development of deeper understanding and facilitates the transferability of knowledge from prior experiences to future tasks. However, specialisation might also hamper growth due to its repetitive nature. Hence, heterogeneity may have a positive and negative impact on learning.[8] The final direction of the impact is difficult to predict and is well-worth testing.

Prior Investment Heterogeneity

One way to measure heterogeneity in the PE environment is by looking at the diversification of investments. Every deal that is executed in another industry can be seen as an additional experience that either adds to a richer understanding of the dynamics in PE investing or dilutes the benefits of specialisation. As we are looking at the effect of prior experience on the current fund's performance, we are interested in a GP's prior industry investment diversification. As with the number of deals, we base our analysis of heterogeneity only on the immediately preceding fund of a GP, due to data availability. Given the ambivalent effect of heterogeneity on performance, we aim to test for the following question:

[8] The fact that heterogeneity might have an ambivalent impact on learning was highlighted by literature, where some sources found positive and others negative effects of current specialisation on the current fund's performance (see literature review in Chapter 2).

Test 3.1: Do GPs with a more diverse industry investment experience perform better as they make more different experiences or perform worse due to missing scope and expertise?

Apart from specialising in industries, a GP may also specialise in regard to other areas. Following Lossen (2006), who looks at the geographic investment diversification of the current fund, we will add a second dimension and look at geographic diversification of the prior fund. On the one hand, wider geographic experience could create broader networks, help with global trend identification, and generate generally-applicable lessons from intercultural interactions. On the other hand, a high geographic investment heterogeneity could dilute the deeper understanding of a specific region's culture, market and processes. Thus, our second test for the *Learning by Stretching* dimension is:

Test 3.2: Do GPs with a more diverse geographic investment experience perform better as they make more different experiences or perform worse due to missing scope and expertise?

Table 1: Overview of Hypotheses

The table presents the hypotheses we aim to test in this thesis, structured by the dimensions Learning by Thinking, Learning by Doing, and Learning by Stretching.

Dimension	Variable	#	Hypothesis
Learning by Thinking	Firm Age	1	The more time has passed since the General Partner's first-time fund, the higher the current fund's performance.
Learning by Doing	Fund Sequence	2.1	The more funds a GP has raised in the past, the higher the performance of its current fund.
	Prior Deals	2.2	The more deals a GPs has done in the prior fund, the more experience he gained which positively drives fund performance of the current fund.
	Prior Successful Deals	2.3	The more deals a GP has done in a prior successful fund, the better the performance of the current fund.
Learning by Stretching	Industry Heterogeneity	3.1	Do GPs with a more diverse industry investment experience perform better as they make more different experiences or perform worse due to missing scope and expertise?
	Geographic Heterogeneity	3.2	Do GPs with a more diverse geographic investment experience perform better as they make more different experiences or perform worse due to missing scope and expertise?

4 Data and Methodology

In this Chapter, we introduce our employed data, variables, and research design. These are building the bases for the results portrayed in Chapter 5.

4.1 Data

This study employs Preqin's Private Capital data set, as of August 2022.[9] Preqin is a commercial database that collected data on more than 8,000 Private Equity funds. Despite the limitation of being partially based on voluntary reporting, Preqin is considered a trustable data source in PE research (Harris et al., 2014).[10] The data from Preqin's database were extended by data from Preqin's website by manually adding deal, industry, and geography data to each fund in our sample. To our best knowledge, this is unique to this study, other studies employing Preqin have not added this fund-level information. Hence, they cannot compare the fund's deal volume and investment heterogeneity with Preqin data.

Sample Derivation

The "Private Capital" data set from Preqin included 8,253 funds with a Buyout or Venture Capital strategy as of August 2022. We filtered and pruned this Full Sample down into two Samples, A and B (see Table 2 below). An extensive version of our filtering process with detailed decision explanations can be found in Appendix 1.

We filtered the Full Sample with three main goals: improve the data reliability and comparability and control for outliers. First, for reliability, we chose to only include liquidated funds since there are manifold potential issues with the Net Asset Value (see Kaplan & Sensoy, 2015; Robinson & Sensoy, 2016; Brown et al., 2019). Second, for comparability, we excluded all funds that had at least one missing variable of the ones subject of our analysis. Further, we decided to only include funds from North America and Europe to diminish the risk that the market environment might affect the impact of experience (Hege et al., 2003). Third, for outlier control, we winsorised the remaining funds simultaneously for MOIC and IRR at the 1st and 99th percentile. With this, we filtered the Full Sample of 8,253 funds down to Sample A with

[9] There are several databases that could have been used for the purpose of this study. Most common data sets include Burgiss, Cambridge Associates, Preqin, Thomson Reuters, Venture Economics (see, e.g., Harris et al., 2014). The authors of this study only had access to Preqin.

[10] Preqin data has been used in many other well-regarded studies (e.g., Phalippou, 2014; Sensoy et al., 2014; Korteweg & Sorensen, 2017). Harris et al. (2014) extensively compared Preqin to the well-regarded Burgiss and Cambridge Associates data sets. Qualitatively, the sets provided similar performance results.

903 funds (which does include first-time funds) and Sample B with 413 funds (which does not include first-time funds).

Table 2: Sample Derivation

The table shows the filtering process, from the Full Sample to Sample A and B in a series of steps. The Full Sample contains 8,253 funds, while Sample A includes 903 funds and Sample B includes 413 funds. The difference between Sample A and B is the exclusion of all first-time funds. While they are still part of Sample A, they are excluded in Sample B.

Steps from Full Sample to Sample A and B	Number of Funds	Funds Excluded
Full Sample - incl. all PE funds	**8,253**	
Only funds with liquidated fund status	2,999	-5,254
Only funds with fund manager from North America or Europe	2,589	-410
Only funds with IRR & MOIC available	2,126	-463
Only funds with Fund Size available & >= 5m	1,989	-137
Only funds with Fund Sequence available. Exclude Sequence and Series inconsistencies	1,585	-404
Only funds with Vintage year of the first-time fund, Firm Age >=0, Vintage 1980-2012	1,299	-286
Only funds with quartile data of the prior fund (unless first-time fund)	1,176	-123
Trimming of 1st and 99th percentile, based on MOIC & IRR	1,138	-38
Only funds with previous deal, geography, and industry data	903	-235
Sample A - incl. first-time funds	**903**	
Exclusion of first-time funds	413	-490
Sample B - excl. first-time funds	**413**	

Sample Overview

In the following, the Samples will be described in terms of Vintage years, fund strategy and regions. They will be compared to show major structural differences.

Table 3: Overview of Funds by Vintage Decade

The table shows the distribution of funds across the Vintage decades from the 1980s to the 2010s. The columns are split into Sample A and B and show the number of funds, the percentage of VC funds, the average fund size in million US Dollars, and the average IRR and MOIC.

	Sample A - incl. first-time funds					Sample B - excl. first-time funds				
Vintage Year	**# of funds**	**% VC**	**Aver. Fund Size (in m)**	**Aver. IRR**	**Aver. MOIC**	**# of funds**	**% VC**	**Aver. Fund Size (in m)**	**Aver. IRR**	**Aver. MOIC**
All Years	903	0.34	473	0.16	1.9	413	0.29	781	0.15	1.9
1980s	70	0.49	251	0.21	2.8	11	0.18	902	0.24	3.4
1990s	396	0.37	382	0.18	2.0	172	0.33	617	0.18	2.0
2000s	426	0.30	596	0.14	1.8	223	0.26	906	0.13	1.8
2010s	11	0.27	411	0.09	1.6	7	0.14	596	0.02	1.5

In this paragraph, we are describing the changes over time within our Samples (see Table 3 above). The majority of our funds have a Vintage year in the 1990s and 2000s. VC funds are losing in sample representation over the decades, compared to Buyout funds. In Sample A, VCs are representing 49% of the PE funds in the 1980s and 30% in the 2000s. The average fund size increases by more than 100% from the 1980s to the 2000s. The average IRR and MOIC are decreasing from 21% to 14% and 2.8 to 1.8, respectively.

Next, we compare Sample B to Sample A because it shows the systematic difference between first-time and later-staged funds. The number of VC funds in Sample B is smaller than in Sample A, possibly showing that, relatively, Buyout funds are more likely to raise second and later-staged funds. The average fund size is nearly twice as high for Sample B, showing that first-time funds are, on average, much smaller than later-staged funds. Further, in the 1980s, 84% of the funds in Sample A are first-time funds, while in the 2000s less than half of the funds are first-time funds, showing the maturing of the industry and its GPs. Last, the average IRR and MOIC are for most decades similar between the two Samples, indicating that first-time funds in our sample do, on average, perform equally well as later-staged funds. The structural differences in our two Samples imply that running our models on both can increase the external validity of our results. A more extensive table, including a detailed breakdown into individual Vintage years, can be found in Appendix 2.

Table 4: Strategy and Region Split for Funds and Fund Managers

The table shows the two data Samples A and B and separates the number of their funds and fund managers (GPs) by region and strategy. The variable region is split into Europe and North America, while the variable strategy is split into PE, which is the sum out of Buyout and VC funds / fund managers.

	Sample A - incl. first-time funds					**Sample B - excl. first-time funds**				
Funds	**PE**	**Buyout**	*(%)*	**VC**	*(%)*	**PE**	**Buyout**	*(%)*	**VC**	*(%)*
Total	903	593	*66%*	310	*34%*	413	294	*71%*	119	*29%*
North America	677	417	*62%*	260	*38%*	318	213	*67%*	105	*33%*
Europe	226	176	*78%*	50	*22%*	95	81	*85%*	14	*15%*
Fund Managers										
Total	521	312	*60%*	208	*40%*	213	142	*67%*	70	*33%*
North America	385	215	*56%*	170	*44%*	164	103	*63%*	61	*37%*
Europe	135	97	*72%*	38	*28%*	48	39	*81%*	9	*19%*

In Table 4, we describe our data Samples' distribution divided by fund strategy and region for funds and fund managers. In terms of region and strategy, the Buyout strategy and North American funds are overrepresented in both Samples, while the VC strategy and European funds are underrepresented. Additionally, VC funds and European funds had relatively more first-time funds, hence relatively more of their funds and fund managers dropped out from Sample A to Sample B. When comparing funds to fund managers, on average, a fund manager raised around 1.7 funds (Sample A). They show similar splits regarding strategy and region.

In comparison to other data sets, the size of our Sample A with 903 PE funds (of which 593 Buyout funds and 310 VC funds) is in line with previous research.[11] Sample B is smaller than most reference sets due to the exclusion of first-time funds. All in all, however, both of our Samples' sizes fall in the spectrum of previous research, hence should have enough observations to produce reliable results.

4.2 Variable Description

This Section provides an overview of the dependent, independent, and control variables entailed in our regression model. Furthermore, Subsection 4.2.4 contains the descriptive statistics for all the variables.

4.2.1 Dependent Variables

As we analyse the effect of experience on PE performance, we need to look at a dependent variable that can be used to measure performance. Academia and the PE industry often rely on two of the main measures to assess the performance of PE funds: IRR and MOIC.[12] Both measures are absolute performance measures based on actual cashflows between GPs and LPs.

The IRR is defined as the discount rate that would make the net present value of all fund cash flows equal to zero. Our data provider Preqin reports the Net IRR which is the IRR earned by an LP after fees and carry. The main benefit of using IRR is that it considers the time value of money. The drawbacks of using IRR, however, are that it can be gamed through the timing of investments and exits as well as measurement problems arise for more complex cash flow patterns (for more details see Doskeland & Strömberg, 2018). Further, it has the disadvantage of becoming very high when capital is returned quickly, which strongly influences the variable's dispersion (see Kaplan & Sensoy, 2015; Braun et al., 2017).

The MOIC is a multiple that is calculated as the sum of fund distributions divided by total cash investment in the partnership. Like the IRR it is also provided by Preqin on a net basis. The advantage of using MOIC compared to the IRR is that it is less prone to return gaming and does not inflate when capital is quickly returned to LPs. Furthermore, the MOIC can always

[11] For example, Robinson & Sensoy (2016) assess Private Equity performance with a data set of 446 Buyout and 260 VC funds. Harris et al. (2022) analyse performance persistence with a larger data set of 2,337 funds, of which 929 are Buyout and 1,408 VC funds. Braun et al. (2017) sample 865 Buyout funds and do not include VC funds.

[12] See Harris et al. (2022) and Robinson & Sensoy (2016). PE research is also using the Public Market Equivalent (PME) as a return measure to overcome drawbacks of the IRR and MOIC (e.g., Kaplan & Schoar, 2005). The PME discounts both distributions and capital calls using the returns from a public market benchmark index as the discount rate. It makes PE investments more comparable by taking the opportunity costs of investing in PE into account. Due to a lack of data and a focus within the PE asset class, the PME is not considered in this analysis.

be calculated regardless of the cash flow pattern. However, it does not consider the time value of money. Since the two metrics, IRR and MOIC, complement each other, we use both in our analysis to get a more holistic picture of the fund returns.

4.2.2 Independent Variables

To test our hypotheses developed in Chapter 3, we use the following six independent variables.

First, we set up the variable *FIRM AGE* to capture the dimension of *Learning by Thinking* (Hypothesis 1). We defined firm age as the difference between the vintage years of a fund manager's first-time and current fund. Hence, at the first-time fund, the age of the GP is zero and increases afterwards with every calendar year. The rational for our calculation is that some of the GPs in our data Sample had other business areas before their PE operations (e.g., Goldman Sachs was founded in 1869, but their first PE fund in our data Sample has 1997 as its Vintage year). With our approach, we believe that the years of active PE investment experience are more accurately approximated.[13]

Second, the variable *FUND SEQUENCE* is used to analyse the dimension of *Learning by Doing* (Hypothesis 2.1). It denotes the number of funds a particular GP has raised, including the current fund. GPs of funds with a higher sequence number have raised more funds and thus are assumed to be more experienced.

Third, we use the variable *DEALS PRIOR* to look at the *Learning by Doing* dimension on a more granular level (Hypothesis 2.2). To set this variable up, we manually looked up the deal data for the prior fund on the Preqin website. We did this for funds with a direct predecessor in our data Sample, based on a fund's sequence. All first-time funds were automatically assigned a value of 0 for this variable. Later-staged funds without deal information for the prior fund are excluded from our Samples A and B.

Fourth, we set up the dummy variable *FIRST QUARTILE PRIOR*. We do this to test the interaction with *DEALS PRIOR* (Hypothesis 2.3).[14] If the previous fund of a GP was in the first-quartile (= a top performer), the dummy variable takes a value of 1 and 0 otherwise.[15] This interaction term we only run on Sample B because first-time funds naturally are missing information about the quartile of their prior fund.

[13] Aigner et al. (2008) argue in a similar way when setting up their firm age variable as experience proxy.
[14] Brown et al. (2019) also also investigated the special properties of first-quartile funds in previous studies with an interaction dummy variable.
[15] Preqin calculated the quartile ranking placing an equal weight on IRR and MOIC. Funds in a particular quartile have an IRR or MOIC equal or above the respective quartile benchmark.

Finally, we calculated the variables *HHI GEO PRIOR* and *HHI IND PRIOR* to measure the heterogeneity of the investment experience (Test 3.1 and Test 3.2). We follow Castellaneta & Zollo (2015) and use the Herfindahl–Hirschman Index (HHI) to measure the prior fund's relative experience heterogeneity.[16] The HHI can, by definition, only take a value between 0 and 1. A fund with an HHI of 1 has invested concentrated in only one geography or industry and hence is assumed to have made more specialised experiences. The closer the HHI to 0, the more diverse the prior investment experience has been. We only run the HHI variables on Sample B because first-time funds naturally miss information about the prior investment heterogeneity since they had no prior fund.

4.2.3 Control Variables

In line with existing literature and the characteristics of our data Samples, we include a range of control variables and fixed effects in our analysis to control for other factors that are known to be related to performance.

First, we control for *FUND SIZE*. Existing research has found fund size to be an important characteristic to capture performance-related factors such as economies of scale and reputation (e.g., Kaplan & Schoar, 2005; Phalippou & Zollo, 2006; Phalippou & Gottschalg, 2009). In line with Kaplan & Schoar (2005) and Hochberg et al. (2007) we use the logarithm as well as the squared logarithm of the variable in our model to account for the assumed concave relationship of fund size with performance.

Second, we include past performance dummy variables as a control factor in our regression.[17] Several studies identify past performance as one potential return predictor (e.g., Harris et al., 2022; Braun et al., 2017).[18] We create four dummy variables, one for the first three performance quartiles of the previous fund and one for previous funds where the quartile information was missing.

Third, following Kaplan & Schoar (2005) we control for the asset class by including a *VC DUMMY* in our model, to account for systematic differences in returns between Buyout and

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[16] To set up the HHI variable, we manually looked up our funds' number of deals per geography and industry on Preqin's website; possible deals' geographies are seven regions: North America, Europe, Asia, Australasia, Middle East, Latin America & Caribbean and Africa. Preqin divides the industries into the following nine categories: Business Services, Consumer Discretionary, Energy & Utilities, Financial & Insurance Services, Healthcare, Industrials, Information Technology, Raw Materials & Natural Resources, Real Estate and Telecoms & Media.

[17] The performance dummy variables are called *FIRST QUARTILE PRIOR*, *SECOND QUARTILE PRIOR*, *THIRD QUARTILE PRIOR*, *NA QUARTILE PRIOR* respectively. The first-quartile represents the top 25% of funds whereas the fourth quartile represents the bottom 25%. The quartile information is obtained from Preqin.

[18] For example, Harris et al. (2022) find that the positive significant impact of persistence has reduced over time. While it is still very relevant for VC funds, PE funds are now less persistent, if at all.

Venture Capital funds. The dummy takes a value of 1 if the fund is a VC fund and 0 otherwise. The classification of funds into Buyout or VC follows Preqins' asset class variable.

Fourth, we consider *Region Fixed Effects* by including a dummy variable to indicate if a GP firm is headquartered in North America or Europe. In doing so, we aim to account for geographical differences in the maturity of the PE market and institutional framework that may affect performance.[19]

Fifth, similar to Phalippou & Gottschalg (2009) and Kaplan & Schoar (2005) we include *Time Fixed Effects* based on Vintage years in our model to account for variables that are constant across firms but vary over time. Past PE performance has shown a high degree of cyclicality, which justifies this control (e.g., Robinson & Sensoy, 2016).

4.2.4 Descriptive Statistics

In this Subsection, we first outline the distributions of the independent and dependent variables and, afterwards, their cross-correlations.

Table 5: Descriptive Statistics of Variables

In the rows, the following table lists the distribution of dependent and independent variables over Samples A and B. In the columns, the Number of Funds, Average, Standard Deviation, and Quartile Distribution are portrayed.

	# Funds	Average	Standard Deviation	Min	25th Percentile	Median	75th Percentile	Max
Sample A - incl. first-time funds								
IRR	903	0.16	0.20	-0.33	0.05	0.13	0.23	1.34
MOIC	903	1.9	1.1	0.1	1.3	1.7	2.4	8.3
FIRM AGE (in years)	903	3.9	5.8	0.0	0.0	0.0	7.0	34.0
FUND SEQUENCE	903	2.5	2.6	1.0	1.0	1.0	3.0	19.0
DEALS PRIOR	903	4.5	9.9	0.0	0.0	0.0	5.0	115.0
Sample B - excl. first-time funds								
IRR	413	0.15	0.20	-0.26	0.04	0.12	0.22	1.27
MOIC	413	1.9	1.1	0.2	1.2	1.7	2.3	8.0
FIRM AGE (in years)	413	8.5	5.8	0.0	4.0	7.0	11.0	34.0
FUND SEQUENCE	413	4.2	3.0	2.0	2.0	3.0	5.0	19.0
DEALS PRIOR	413	9.8	12.8	1.0	3.0	6.0	11.0	115.0
QUARTILE PRIOR	413	2.2	1.0	1.0	1.0	2.0	3.0	4.0
HHI GEO PRIOR	413	0.9	0.2	0.3	0.9	1.0	1.0	1.0
HHI IND PRIOR	413	0.5	0.3	0.1	0.3	0.5	1.0	1.0

While Sample A and B are distributed similarly over *IRR* and *MOIC*, they are notably different for *FIRM AGE*, *FUND SEQUENCE*, and *DEALS PRIOR*. Sample B holds older fund managers, and higher sequenced fund managers, and their previous funds have a higher number

[19] Strömberg et al. (2003) document differences in contracting between the US and twenty-three non-U.S. countries. Hege et al. (2003) find performance differences between certain PE investments in Europe and North America. Braun et al (2017) also control for region fixed effects in their analysis of performance persistence.

of deals on average. This difference is driven by the exclusion of first-time funds, which have a *FIRM AGE* and *PRIOR DEALS* of 0 and a *FUND SEQUENCE* of 1.

For both Samples, *IRR* and *MOIC* are on average positive, with 16% and 1.9 (Sample A) and 15% and 1.8 (Sample B), respectively. The extreme values of Min and Max would be even larger if the Samples were not already winsorised at the 1^{st} and 99^{th} percentile. Compared to the Average, the Standard Deviation of the *IRR* is significantly higher than that of the *MOIC*, indicating a greater dispersion. For the other variables, Sample B will be described. In Sample B, the average firm was 8.5 years old, had raised 4.2 funds, and had done 9.8 deals in their previous fund. The previous fund's investments were, on average, very geographically focused, while their industry investments were generally more diversified. This industry diversification points towards more generalists being part of the sample than specialists, which is in line with previous research (e.g., Ljungqvist & Richardson, 2003). When looking at outliers, it shows that all variables are quite strongly skewed, except for heterogeneity and *QUARTILE PRIOR*. *QUARTILE PRIOR*'s distribution is not distributed as one would expect (see histograms in Appendix 3). When analysing the Full Sample, we find that 23% of current funds are in the fourth quartile. However, of all funds in the Full Sample, only 17% had a prior fund in the fourth quartile. This could suggest that while fourth-quartile funds are generally represented, they are less likely to raise a follow-up fund. In Sample B, only 17% of the current funds are fourth-quartile, showing that during filtering for missing variables, relatively more fourth-quartile funds were excluded (23% to 17%). Further, in Sample B, only 13% of all funds had a previous fund in the prior fourth-quartile, showing again that fourth-quartile funds are less likely to raise a follow-up fund (17% to 13%).

For analysing the pairwise correlation of our variables, we created a correlation matrix with the Pearson Correlation Coefficient in Appendix 4. We verify that no correlations between our independent variables are too high, making us confident that our measures capture different dimensions of experience. The highest positive correlation coefficients in Sample B are between *MOIC* and *IRR* (0.79) and *FUND SEQUENCE* and *FIRM AGE* (0.72), both statistically significant at the 1% level. The high correlations are intuitive since *IRR* and *MOIC* are both directly related to the fund's payoff, and *FIRM AGE* and *FUND SEQUENCE* are both related to the GP's first-time fund.

4.3 Research Design

To test for the hypotheses outlined in Chapter 3, we employ a multiple linear regression in line with its extensive usage in the PE literature (e.g., Schmidt et al., 2004; Kaplan & Schoar, 2005; Phalippou & Zollo, 2006; Phalippou & Gottschalg, 2009). With the variables described in Subsection 4.2, we set up the model shown in equation (1) below.

$$\begin{gathered} Y_i = \alpha + \beta_1\, FIRM\ AGE_i + \beta_2\, FUND\ SEQUENCE_i + \ \beta_3\, DEALS\ PRIOR_i \\ + \beta_4\, DEALS\ PRIOR_i *\ FIRST\ QUARTILE\ PRIOR_i + \beta_5\, HHI\ GEO\ PRIOR_i \\ + \beta_6\, HHI\ IND\ PRIOR_i + CONTROLS_i + \varepsilon_i \end{gathered} \tag{1}$$

The dependent variable Y_i represents the fund performance measure which can be both *MOIC* or *IRR*.[20] The right-hand side of the equation consists of our independent and control variables. The first three independent variables are *FIRM AGE, FUND SEQUENCE* and *DEALS PRIOR*.[21] The fourth independent variable is the interaction term of *PRIOR DEALS* with the *FIRST QUARTILE PRIOR* dummy variable. The fifth and sixth independent variables are the two prior investment heterogeneity variables *HHI GEO PRIOR* and *HHI IND PRIOR.* In addition, we include all control variables discussed in Subsection 4.3 to control for other factors that might affect performance.[22] The last term ε_i is the error term that accounts for the unexplained difference between the observed values of the dependent variable and the results predicted by the model.

Our main model operates on our Sample B of 413 funds. Due to the high requirement for available fund data in our main model, a large number of funds were filtered out during the sample generation (see Section 4.1). When only interested in the first three variables *FIRM AGE, FUND SEQUENCE* and *PRIOR DEALS* as independent variables, we can operate on a sample more than twice as large with 903 funds (Sample A). Consequently, to see if our results also hold for the larger sample, we additionally run a reduced version of the main model.

[20] Due to skewness in both dependent variables, we also tested a logarithmic transformation of MOIC and IRR. The regression results before and after the transformation are similar. Hence, we use the linear form of the variables in the main text for interpretation purposes. The results with the dependent variables in logarithmic form are discussed in our robustness checks in Section 5.2 and can be found in Appendix 6.

[21] In accordance with Woolridge (2016) we use the original form of the age variable in our model. Further, we looked at the results of our model with using the natural logarithm of *FUND SEQUENCE* and *PRIOR DEALS* and found similar results. For ease of interpretation, we decided to use the original form in our model.

[22] As described in Chapter 4, we control for log(*FUND SIZE*), log(*FUND SIZE*)^2, *VC DUMMY*, the prior performance quartiles as well as *Region* and *Time Fixed Effects*. The variables are not included in equation (1) for readability purposes.

To ensure the validity of our models, we carried out a series of tests. First, in line with Kaplan & Schoar (2005), we tested for heteroskedasticity in the variance of the residuals. For this, we applied the Breusch-Pagan Test and rejected homoskedasticity at a 1% level. Hence, in all of our models, the standard errors of the reported regressions are corrected for heteroscedasticity. Second, we tested for multicollinearity in our independent variables by calculating Variance Inflation Factors (VIFs) to ensure the validity of our estimators. The test shows that multicollinearity does not appear to be a problem in our models (see Appendix 5).[23] Last, to overcome problems associated with large outliers, we winsorise the data based on the dependent variables at a 1% and 99% level (see Section 4.1).

[23] Following Woolridge (2016), we use the commonly employed rule that a VIF below 10 does not implicate a problem with multicollinearity. The only two variables that are above this threshold are log(*FUND SIZE*) and log(*FUND SIZE*)^2. This is natural as these two controls are based on the same variable. We include both to capture the concave relationship of size with performance in our model which was found in previous studies (e.g., Kaplan & Schoar, 2005).

5 Empirical Results

This Chapter depicts the empirical results of our analysis. The regression output is presented in Table 6. In Section 5.1, the results are described and discussed. Subsequently, Section 5.2 deals with the robustness of the results.

Table 6: The Effect of Experience on PE Fund Performance

The table shows the OLS regression output of analysing the effect of General Partner experience on the performance of Private Equity funds. We use two data samples composed of 903 funds (Sample A, including first-time funds) and 413 funds (Sample B, excluding said first-time funds). The dependent variables in our model are MOIC and IRR. To account for return outliers, the data was winsorised at the top and bottom 1% of the sample. To proxy experience we use the five independent variables FIRM AGE, FUND SEQUENCE, DEALS PRIOR, HHI GEO PRIOR, and HHI IND PRIOR, as well as an interaction term of DEALS PRIOR and FIRST QUARTILE PRIOR. In addition, we control for a range of other variables that may affect performance: the natural logarithm of FUND SIZE and of FUND SIZE^2, the investment strategy (VC DUMMY) and the prior fund's quartile. All regressions include Region and Time Fixed Effects. Standard errors are adjusted for heteroskedasticity.

	Sample A (including first-time funds)		**Sample B** (excluding first-time funds)	
Variables	**(1) MOIC**	**(2) IRR**	**(3) MOIC**	**(4) IRR**
FIRM AGE	0.03**	0.00	0.02**	0.00
	(0.01)	(0.00)	(0.01)	(0.00)
FUND SEQUENCE	-0.01	0.01	-0.03	0.01
	(0.02)	(0.00)	(0.02)	(0.00)
DEALS PRIOR	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
*DEALS PRIOR * FIRST QUARTILE PRIOR*			-0.02**	-0.00
			(0.01)	(0.00)
HHI GEO PRIOR			-0.02	0.01
			(0.27)	(0.06)
HHI IND PRIOR			-0.42*	-0.04
			(0.21)	(0.04)
log(FUND SIZE)	-0.14	0.01	-0.16	0.03
	(0.16)	(0.03)	(0.23)	(0.04)
log(FUND SIZE)^2	0.00	-0.00	0.00	-0.00
	(0.01)	(0.00)	(0.02)	(0.00)
VC DUMMY	-0.42***	-0.08***	-0.23	-0.06*
	(0.10)	(0.02)	(0.18)	(0.03)
FIRST QUARTILE PRIOR	0.60***	0.12***	0.73***	0.13***
	(0.16)	(0.03)	(0.19)	(0.03)
SECOND QUARTILE PRIOR	0.28*	0.04	0.27	0.04
	(0.15)	(0.03)	(0.17)	(0.03)
THIRD QUARTILE PRIOR	0.21	0.02	0.29*	0.03
	(0.16)	(0.03)	(0.17)	(0.03)
NA QUARTILE PRIOR	0.33**	0.07***		
	(0.15)	(0.03)		
CONSTANT	3.28***	0.16*	3.59***	0.24*
	(0.44)	(0.09)	(0.77)	(0.14)
Observations	903	903	413	413
Time fixed effects	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES
Adjusted R-squared	0.15	0.13	0.21	0.18

*, **, *** indicate 10%, 5% and 1% significance level, respectively.
Standard errors are in parentheses and are adjusted for heteroskedasticity.

5.1 Discussion

In the following, we present and discuss the results of the statistical analysis portrayed in Table 6. The table shows the output for four different regressions. We ran our reduced model in regression (1) and (2) on Sample A and the main model in regression (3) and (4) on Sample B (see Chapter 4 for a detailed description of the data, variables, and regression models). Hence, each model has run on both dependent variables, *MOIC* and *IRR*. Looking at the general fit of the models, the adjusted R-squared in all regressions ranges from 0.13 to 0.21. Although low, these numbers are in line with previous regressions on PE fund returns (e.g., see Harris et al., 2022; Hochberg et al., 2007).

The results for *MOIC* and *IRR* regressions vary in terms of their significance. While the results on *MOIC* are statistically significant for many variables, this does not hold for the *IRR*. Although the inconsistency seems surprising, past studies had similar issues with differing significant levels of variables for *MOIC* and *IRR* (e.g., Sensoy et al., 2014). The IRR measure has the disadvantage that it can be gamed through timing cashflows (see Doskeland & Strömberg, 2018). Through this, the IRR may take substantially positive values when capital is returned quickly, which strongly influences the variable's dispersion (see Kaplan & Sensoy, 2015; Braun et al., 2017). In our paper, this can be seen by the substantially higher standard deviation relative to the average of the *IRR* compared to the *MOIC* (see Descriptive Statistics in Subsection 4.2.4). Given the named weaknesses of the IRR and the non-significant results in our study, we will focus on the models with *MOIC* as their dependent variable. In terms of Samples, Sample A served to confirm the results on *FIRM AGE*, *FUND SEQUENCE* and *PRIOR DEALS* on a significantly larger and structurally different sample (including first-time funds). Since the results for our independent variables are consistent, we will focus on Sample B, which runs on our main model that includes all independent variables simultaneously. Consequently, our discussion is based on the findings of our regression (3).

Three of our experience proxies are statistically significant: *FIRM AGE* with a positive coefficient, the interaction term of *PRIOR DEALS* and *FIRST QUARTILE PRIOR* with a negative coefficient, and *HHI IND PRIOR* with a negative coefficient. The experience proxies *FUND SEQUENCE, DEALS PRIOR,* and *HHI GEO PRIOR* are not significant. In the following paragraphs, we will first discuss the implications of the significant independent variables. Subsequently, the results of the other independent variables are briefly summarised.

Firm Age

The first significant independent variable is *FIRM AGE*. Based on the *Learning by Thinking* theory, we expected that older GPs have gained more experience than younger GPs. This experience advantage should lead older GPs to have higher fund returns (Hypothesis 1).

Indeed, we can confirm this hypothesis. The coefficient of *FIRM AGE* is positive and has a significant effect at the 1% level in regression (3) with an effect of 0.02. Hence, for every year that a GP is older, the *MOIC* increases by 0.02 on average, all else equal. The positive effect of the age of a GP in our regressions is in line with Aigner et al. (2008) but contradicts the insignificant findings of Schmidt et al. (2004) and Lopez-de-Silanes et al. (2015). This difference might be explained by three major differences between their papers and ours. Compared to Schmidt et al. (2004), we calculate *FIRM AGE* in a way that reduces noise. Instead of starting to count the firm age from a GP's founding year, we are starting at the Vintage year of their first-time fund. The motivation is that older firms might decide to raise a Private Equity fund at some point, be it as a new investment arm for their clients or as a corporate VC fund. Although they have existed as a company for many years at that moment, they do not have any experience with managing Private Equity funds. Consequently, we believe to account more accurately for the actual PE experience gained with our calculation. Second, Lopez-de-Silanes et al. (2015) run their regression on deal level, whereas our analysis is based on fund level. While deal-level data is more granular, it might also be more susceptible to strong outliers, which might thwart the impact of age. Third, we employ more recent data in our study, and therefore, the difference may reflect a systematic change in the prediction power of age over time with the increasing maturity of the PE industry. To sum up, the age variable is significant despite the many other experience variables included in our *MOIC* regression models, which shows that age as an experience measure matters for performance.

Success of Prior Deals

The second significant effect in our regression models is the interaction term of *PRIOR DEALS* and *FIRST QUARTILE PRIOR*. Based on the *Learning by Doing* dimension, we test whether the success of the prior fund changes the impact of the effect of the prior fund's number of deals on performance. We expected the effect to be positive since prior successful funds may have more best-practices to rely on or may inherently be better at learning (Hypothesis 2.3).

First, we looked at the two variables separately. *PRIOR DEALS* alone is not significant in any of our regression specifications. Therefore, the prior fund's deal amount is no useful predictor for the current fund's returns. *FIRST QUARTILE PRIOR* is significant at a 1% level and positively affects *MOIC* by 0.73 on average. Hence, having had a prior successful fund is a positive predictor for the current fund.[24] Then, we looked at the two variables in interaction. The interaction term of *FIRST QUARTILE PRIOR* and *PRIOR DEALS* is statistically significant at the 5% level with a negative effect of -0.02 on *MOIC*. Consequently, the current fund's *MOIC* is reduced for every deal the former first-quartile fund had, each deal reducing the generally positive impact of *FIRST QUARTILE PRIOR*. Accordingly, we reject our Hypothesis 2.3 that more deals in a successful fund lead to better subsequent performance.

This seems surprising since we expected the GPs to learn even more from more previous successful experiences. We will provide two potential explanations for this result. The first potential explanation is the well-established concept of overconfidence (see, e.g., Zacharakis & Shepherd, 2001; Graves & Ringuest, 2018). With every extra deal of the previous successful fund, the GP might have become more confident.[25] This confidence, in turn, might lead the GP to overlook relevant factors in subsequent deals, limit their search to the previous successful areas, or engage in excessive risk-taking. Our second potential explanation is that the results may not actually be driven by experience at all. Rather, they might be the result of a selection bias. GPs that had a successful prior fund and had many deals might have kept the strategy of doing many deals. If having many deals impacts a fund negatively, this would explain the negative effect of the prior fund's number of deals that we are observing. To answer if the current number of deals affects the current fund's performance, we ran a robustness test, which can be found in Section 5.2. The test showed that the number of current deals does not impact the *MOIC* and that the interaction term remains statistically significant. Hence, the observed effect is not driven by the number of deals of the current fund. We conclude that the effect we are seeing might, in fact, be an experience effect driven by overconfidence.

Prior Industry Heterogeneity

The third significant variable is *HHI IND PRIOR*. By including this variable in our model, we aimed to test whether specialised or diversified prior experiences are better for future fund performance (Test 3.1). As shown in Table 6, the coefficient for *HHI IND PRIOR* is negative, with a magnitude of -0.42 on the *MOIC* at the 10% significance level in model (3). Hence, if

[24] This finding is partially in line with the latest paper of Harris et al. (2022). The beforementioned states that performance persistence is likely not significant anymore for Buyout funds, but still very significant for VC funds.
[25] Our data does not contain deal-level information; hence we do not know how many of the deals of the previous fund were actually successful. We do know, however, that the fund in general was more successful. Hence, with this argument, we would assume that, on average, every single deal in a prior successful fund made the GP more overconfident.

the industry specialisation, measured by the HHI, increases by one standard deviation, the *MOIC* decreases by 0.13 on average.[26]

The positive effect on returns of having invested in a variety of industries with the prior fund might be explained by two reasons. First, a generalist has learned how to invest into different industries leading to more flexibility in seizing future investment opportunities. Second, a former generalist may have acquired a broader and eclectic set of best-practices that can now be applied in operational value creation.

On the other hand, our result may not be driven by an experience effect. Instead, it might be driven by the current fund's specialisation. Funds with a prior generalist fund might be more likely to raise a succeeding generalist fund. If a current fund's specialisation level impacts the current fund's performance, our result might be driven by heterogeneity persistence. To test this, we run a robustness check and control for the specialisation of the current fund. As can be seen in Appendix 8 and Section 5.2, prior industry heterogeneity loses its statistical significance. Hence, the prior fund's industry heterogeneity is not a good predictor of future performance. Accordingly, the answer to our test is that prior industry heterogeneity neither positively nor negatively impacts returns.

Fund Sequence

The first independent variable that was insignificant from the start is *FUND SEQUENCE*. Based on our insignificant results, we reject our Hypothesis 2.1 that GPs that raised more funds in the past are more likely to perform well in the current fund. This variable tried to capture the *Learning by Doing* dimension.

Our finding aligns with Lopez-de-Silanes et al. (2015) and Hochberg et al. (2007), who find no significant effect of fund sequence. It, however, contradicts the study of Kaplan & Schoar (2005) or Sensoy et al. (2014), who do find a significant positive effect of fund sequence on fund returns. The most likely explanation is that opposed to those two studies, we included more than one experience dimension in our models and not only fund sequence. One of these variables we include is *FIRM AGE*, which is highly correlated with *FUND SEQUENCE* (0.72 Pearson Correlation Coefficient, see Subsection 4.2.4) and, therefore, might absorb some of its effect. Although *FIRM AGE* and *FUND SEQUENCE* are highly correlated, we keep both in our models as they capture uniquely different learning channels, which is the central part of our

[26] The standard deviation of HHI IND PRIOR is 0.30 (see Subsection 4.2.4). Multiplying 0.3 * 0.42, the result of moving towards specialisation by one standard deviation is 0.126 MOIC.

analysis. To test our results against the other studies, we dropped the variable *FIRM AGE* from our main model (see Appendix 7). We do indeed find significant results for *FUND SEQUENCE* in most of the regressions. Interestingly, as with Sensoy et al. (2014), *FUND SEQUENCE* has a higher significance for the *IRR* than for the *MOIC* regressions.

Our results imply that while *FUND SEQUENCE* might be employed as a predictor of future success, it is dominated by the *FIRM AGE* variable. Hence, if the Vintage years of the first-time fund and of the current fund are available, *FIRM AGE* should be rather used as performance predictors for future fund performance.

Prior Deals

Based on our third Hypothesis 2.2, we expected that a higher number of prior deals would lead to better performance. In contrast to our expectation, we reject this hypothesis and the effect of the number of the prior fund's deals on a subsequent fund's performance. The coefficient on prior deals is consistently positive but insignificant in all of our regression specifications.

Hence, the second measure within the *Learning by Doing* dimension also appears to be an insignificant performance predictor. However, as mentioned in this Section before, the third variable, the interaction term of *PRIOR DEALS* with *FIRST QUARTILE PRIOR*, is significant. *PRIOR DEALS'* insignificance is an indication that only looking at the experiences gained from the number of deals in the prior fund is not sufficient to derive meaningful conclusions about future performance. If interacted with prior quartiles, this, however, changes and deals become a significant predictor.

Prior Geography Heterogeneity

The final independent and insignificant variable is *HHI GEO PRIOR*. To our best knowledge, there is no literature on prior PE experience heterogeneity (as discussed in Chapter 3). Hence, we wanted to test whether a higher experience heterogeneity, measured by the relative dispersion of geographies of the previous fund's investments, does affect performance (Test 3.1). Against our expectations, we did not find any significant effect, neither positive nor negative. The insignificant results are most likely due to the very broad division of the variable into seven areas that are roughly matching the continents. To account for actual geographical differences (such as the political, legal, economic, or cultural environment), a more specific analysis would be required. However, this study did not have access to this type of information.

5.2 Robustness Tests

In this Section, we summarise the additional analyses we conducted to determine whether our findings are robust.

The first robustness check concerns our dependent variables, *MOIC* and *IRR*. Following Kaplan & Schoar (2005), we included the dependent variables in their natural form in our main model. This also served the purpose of a more intuitive interpretation. A common practice in finance is to use the natural logarithm of a variable to reduce skewness and increase the precision of the estimators (e.g., Lossen, 2006; Aigner et al., 2008).[27] The dependent variables in our data set are moderately right-skewed (1.76 for *MOIC* and 1.59 for *IRR* in Sample B). Therefore, we rerun all four main regressions transforming *MOIC* and *IRR* with the natural logarithm. The results can be found in Appendix 6. The general goodness of fit of the models measured by the adjusted R-squared slightly increases in the transformed regressions. Naturally, the magnitude of the coefficients is smaller in the regressions after the logarithmic transformation. The significance levels of the already previously significant *FIRM AGE* coefficients slightly increase, with all its coefficients still being positive. The coefficient of the interaction term of *DEALS PRIOR* with *FIRST QUARTILE PRIOR* also remains negative and significant at the 10% level. Our measure of diversified industry experience with *HHI IND,* which had previously been significant at a 10% level (0.051 significance), loses its significance. The other independent variables do not change noticeably in terms of statistical significance.

The second robustness check is regarding the Herfindahl-Hirschman Index. Lossen (2006) raised the question if this index might not be the appropriate measure of diversification across geographies and industries. The effect of experience heterogeneity might not depend on the relative distribution of a fund's investments across geographies or industries but instead might depend only on the number of geographies or industries a PE fund invests in. To test this assumption, we ran our main model again, replacing the variables *HHI GEO PRIOR* and *HHI IND PRIOR* with *GEO COUNT PRIOR* and *IND COUNT PRIOR*, which count the total number of geographies and industries the prior fund of a GP invested in. The regression results with the *COUNT* variables are similar to the regressions using the *HHI* variables with respect to the

[27] In addition, we conducted a Box-Cox test to test for the right transformation of the dependent variables to follow a normal distribution (Box & Cox, 1964). The output of the Box-Cox test is the estimated parameter λ. Following Lossen (2006) a λ equal to 1 suggests to keep the linear form, a λ equal to 0 suggests a logarithmic transformation of the variable. The results of our tests are a λ of 0.2 for MOIC and a λ of -1 for IRR. Since both numbers are closer to 0 than to 1, we decided to run our models in a robustness check with the dependent variables in the natural logarithm.

significance and sign of the coefficients (see Appendix 8). This shows the robustness of our results in the original model, where industry specialisation is negatively correlated and significant for *MOIC*. The prior geographic specialisation remains statistically insignificant.

The third robustness test serves as the analysis of whether our significant results on the coefficient of prior industry heterogeneity are driven by a selection or experience effect (see discussion in Section 5.1). Hence, it is useful to control for the current fund's heterogeneity. To do so, we created a variable *SPECIALIST DUMMY* that takes the value of 1 if a current fund only invested in one industry (= specialist) and of 0 otherwise. As not all funds in our Sample B have deal information about the current fund, which is necessary to set up the dummy, our sample reduces from 413 to 387 funds for this analysis. The results of the robustness check are shown in the regressions (15) and (16) in Appendix 8. Neither the coefficient on our *HHI IND* variable nor the variable on the *SPECIALIST DUMMY* are significant. Hence, it is shown that our results are not robust and that the heterogeneity of prior or current industry experience may not be a driver of performance as assumed previously.

The last robustness check regards the interaction term of *PRIOR DEALS* with *FIRST QUARTILE PRIOR*. In order to test whether our significant results on the interaction term are driven by the current fund's deals or an experience effect (see discussion in Section 5.1), we run an additional regression on our main model, including a new control variable *DEALS* for the number of deals in the current fund (see Appendix 8). As in the previous robustness check, the model ran on the reduced sample of 387 funds with deal information for the current fund. The regression results (regression 17) show that the interaction term of *PRIOR DEALS* and *FIRST QUARTILE PRIOR* is still negative and statistically significant. Hence, the results on the interaction term are robust and support the experience-based explanation with a negative effect of a high number of prior successful deals.

6 Conclusion

This thesis studied the effect of General Partner experience on Private Equity fund returns. Based on the existing literature on PE fund performance and organisational learning theory, we developed four hypotheses and two tests to analyse the effect of experience on fund performance.

Looking at the results, we first show that the age of a GP has a significant and positive effect on fund returns. Instead of the pure number of experiences made, our results suggest that enough time to reflect on experiences and subsequently drive change is important to improve investment decisions. Second, we find a significant and negative effect of a prior first-quartile fund's number of deals. The effect is robust if we control for the number of deals in the current fund. This finding is counterintuitive since more experience is usually regarded as superior to less experience. However, it might be explained by the assumption that a high number of good experiences in the prior fund cause misleading confidence which in turn harms future performance. Separately from each other, the prior first-quartile performance has a strong and significant positive impact on fund returns, while the prior fund's deals have no significant effect. Third, we find a positive effect of the prior fund's industry diversification on the subsequent fund's return. This implies that a GP might learn more from diversified experience as compared to specialised experience. However, this result is not robust. Hence, it should be treated with caution. The remaining two independent variables, fund sequence and the prior fund's geographic heterogeneity, are not significant in our joint models.

For our study, we adapted the experience framework of Lapré & Nembhard (2011). Its first dimension is *Learning by Thinking* which describes the importance of time for reflection to learn and improve. In our study, this dimension, measured by the PE firm's age, proved the most reliable. The second dimension, *Learning by Doing*, looked at task repetition. Our results suggest that, in PE, solely looking at the prior fund's number of experiences is not sufficient. However, in combination with the success of the experience, the *Learning by Doing* dimension has a significant but unexpectedly negative effect. Last, *Learning by Stretching* measured how the heterogeneity of past experiences influences performance. Although our main model suggested a positive relation of a more diverse experience, after running robustness checks, the dimension did not appear significant for predicting PE fund returns anymore.

The discussed results are based on MOIC as our employed performance metric. When switching the metric from MOIC to IRR, the results for most of our variables lose their significance. This inconsistency between performance metrics has also been found in previous studies (e.g., Aigner et al., 2008; Sensoy et al., 2014). The IRR measure has the disadvantage that it can be gamed through timing cashflows and may take substantially positive values when capital is returned quickly, which strongly influences the variable's dispersion (see Kaplan & Sensoy, 2015; Braun et al., 2017, Doskeland & Strömberg, 2018).

Our thesis contributes to the current academic literature in three main ways. First, our study is unique in having a dedicated focus on experience and jointly analysing the interaction of multiple experience proxies in one study. Second, we connect organisational learning theory with PE experience and employ two experience proxies beyond the commonly applied that have, to the best of our knowledge, not been tested in relation to fund returns before. The two proxies are lagged heterogeneity variables for geography and industry. Third, we use a more recent data Sample than previous studies, which accounts for the potential change in the prediction power of experience proxies over time.

Apart from the academic contribution, our main findings also have a practical implication for Limited Partners, helping them to make investments in the most promising funds in the evermore complex and growing PE landscape. Our findings suggest that, on average, a fund performs better for every additional year a PE firm exists. Hence, age can be applied as one important criterion when choosing the right fund to invest in. However, it is important to highlight that LPs should make their decisions in combination with other significant performance drivers. Our models point significantly and strongly towards a fund's strategy and, if available, its firm's past performance and quartiles.

The findings of this study have to be seen in the light of potential limitations. First, by using our experience framework based on Lapré & Nembhard (2011), we think that we covered a sufficient spectrum of experience measures and associated learning channels. However, our models only consider the organisation's, but not the individual's, experience. Yet, the individual's experience is an important level in organisational learning theory too. Due to data availability restrictions, we could not investigate experience factors on a more granular level.

The second limitation concerns the completeness and quality of the data used for our analysis. PE is, in its nature, private and its data is difficult to access. We used the commercial database Preqin with a comparably large sample of about 8000 PE funds. Still, it is not guaranteed that this sample is representative of the general PE landscape. Databases such as Preqin are usually subject to a sample selection bias as poor-performing funds are generally less willing to report their performance. Hence, our results may be upward biased. Apart from this, many data points were missing, which caused a high reduction in the number of funds after our filtering process, further questioning the representativeness of our results. Moreover, the investment history of many GPs in our data set was incomplete. Consequently, we were not able to look at the full deal and experience heterogeneity history of a GP but had to proxy it by looking at the directly previous fund only. Although more recent experiences may be more relevant for performance, the full investment history would also be insightful to study from an organisational point of view. Despite these shortcomings, we think that our thesis sheds meaningful light on the effects of experience as a performance driver in Private Equity and can be used as helpful guidance for investors in which funds they may invest in the growing PE landscape.

This thesis also calls for future research to better understand the effect of experience on the performance of PE funds and simultaneously may overcome the limitations in our study. First, future research with a larger and more detailed database could allow investigating experience on a deal level with more exact variables on, for example, firm age at investment, the exact number of prior deals before the investment, or previous experience heterogeneity at the time of investment. Also, other performance metrics, such as the Public Market Equivalent as introduced in 2005 by Kaplan & Schoar, would be interesting to analyse to add a relative performance angle. Second, future research could look at experience not only on an organisational level but also on an individual's level. This would allow to add experience proxies that are investment professional related, such as education, age, years in the industry, or participated auction rounds. This could support LPs in their assessment of a GP's (leadership) team.

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Appendix

Appendix 1: Filtering Process

Step one excludes all not-liquidated funds (-5,254 funds), hence making the return data more reliable by excluding the not-yet liquidated firms that only report estimated Net Asset Values. The question of the reliability of Net Asset Values is highly debated. While Robinson & Sensoy (2016) suggest that Net Asset Values are largely reliable, except for in periods of fundraising, Brown et al. (2019) report that underperforming fund managers tend to inflate their interim performance during their fundraising stage, while overperforming fund managers tend to be too modest with their valuations. Kaplan & Sensoy (2015) agree that "smaller, younger, and more poorly performing ones are aggressive in reporting their Net Asset Values when they are fundraising". To reduce the uncertainty, we exclude all non-liquidated funds. In **step two**, the range of geographic headquarters is limited by excluding all GPs not headquartered in Europe and North America (-410 funds), hoping to increase the treatment sample's homogeneity of reactions to experience at the same time. Further, we assume that the data availability and reporting standards are more comparable across those two regions. In **step three**, the IRR & MOIC availability is ensured by dropping 463 funds that were lacking data for one, the other, or both. **Step four** deals with the availability of fund size (- 112 funds) and the exclusion of funds below 5 million US Dollar (-25 funds), in alignment with Kaplan & Schoar (2005). **Step five** excludes funds without fund sequence (-16 funds) and funds that had sequence available, but with apparent data quality issues on the variable (-388 funds).[28] **Step six** ensures that all fund managers in the data sets have available data on the Vintage year of the first-time fund of that fund manager (excluding 263 funds). Further, all funds before 1980 were removed (-8 funds), just like Kaplan & Schoar (2005), who similarly had only too few funds in their data set for the period before 1980. Also, all funds with a Vintage after 2012 were removed (-12 funds), also due to limited data availability. Further, to ensure the quality of the data, all firms with a single fund with negative firm age have been excluded. (1 firm, 9 funds). **Step seven** excludes all funds that do not have quartile information from their previous fund (-123 funds). First-time funds (the first fund a fund manager has ever raised, which have the fund sequence number of 1) are not excluded, however.

[28] While most funds had more "Fund Number (Overall)" (Henceforth "fund sequence") than "Fund observations (Series)" (Henceforth "fund series"), for some fund managers this relationship was inverted. This posed an issue, since the fund sequence, in theory, should be the higher one or at least similar high one of the two variables. Fund sequence describes the number of funds that were raised by the fund manager in total, including the current fund. Fund series, on the other hand, describes the number funds that were raised within a specific fund series. Hence, all fund managers were excluded that had a fund with higher fund series than fund sequence.

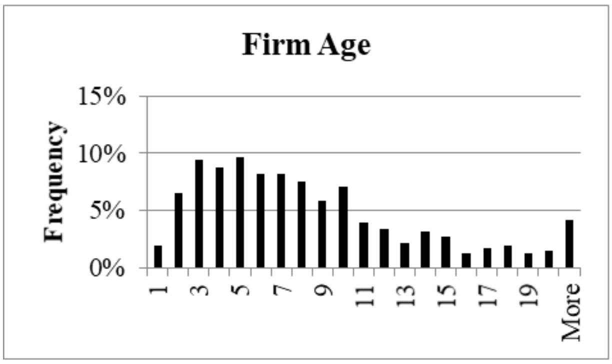
Appendix 2: Funds by Vintage Year

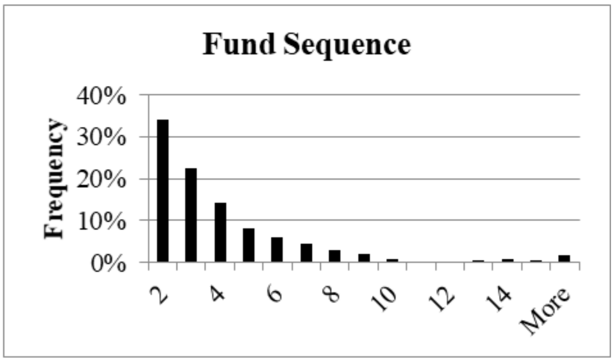
The rows in the following table show the distribution of funds across the Vintage years 1980 to 2012. Further, they show the decade-aggregation for the 1980s to the 2010s. The columns are split into Data Sample A and B. They detail the number of funds, the percentage of VC funds, the average fund size in million US Dollars, and the average IRR and MOIC.

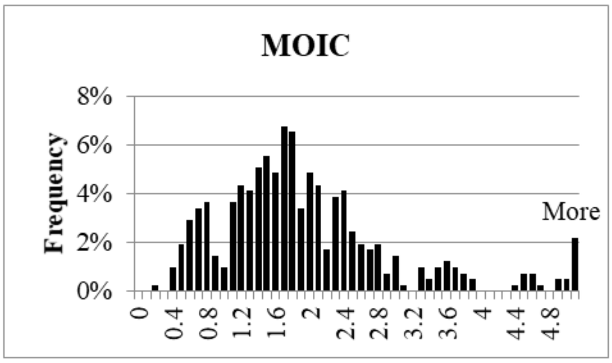
	Sample A - incl. first-time funds					**Sample B - excl. first-time funds**				
Vintage Year	**# of funds**	**% VC**	**Aver. Fund Size (in m)**	**Aver. IRR**	**Aver. MOIC**	**# of funds**	**% VC**	**Aver. Fund Size (in m)**	**Aver. IRR**	**Aver. MOIC**
All Years	903	0.34	473	0.16	1.9	413	0.29	781	0.15	1.9
1980s	70	0.49	251	0.21	2.8	11	0.18	902	0.24	3.4
1990s	396	0.37	382	0.18	2.0	172	0.33	617	0.18	2.0
2000s	426	0.30	596	0.14	1.8	223	0.26	906	0.13	1.8
2010s	11	0.27	411	0.09	1.6	7	0.14	596	0.02	1.5
1980	2	0.50	29	0.16	2.8	0	-	0	-	-
1981	0	-	0	-	-	0	-	0	-	-
1982	2	0.50	186	0.52	3.2	1	-	323	0.39	3.3
1983	4	0.25	143	0.30	2.5	1	-	341	0.15	2.8
1984	8	0.63	164	0.28	3.1	1	-	989	0.29	4.8
1985	10	0.80	73	0.16	3.2	1	1.00	65	0.20	2.9
1986	11	0.45	174	0.17	2.6	3	-	500	0.17	3.0
1987	11	0.55	625	0.12	2.4	2	-	3149	0.20	3.8
1988	10	0.30	374	0.20	2.9	0	-	0	-	-
1989	12	0.33	166	0.25	2.8	2	0.50	206	0.34	3.6
1990	19	0.21	192	0.26	2.9	4	0.50	101	0.27	2.9
1991	5	0.20	188	0.33	2.7	2	0.50	93	0.34	2.8
1992	16	0.31	204	0.20	2.1	5	0.40	165	0.29	2.8
1993	19	0.32	184	0.34	2.8	6	0.17	302	0.51	4.0
1994	39	0.26	297	0.21	2.2	12	0.33	469	0.28	3.0
1995	31	0.42	315	0.25	2.2	12	0.08	579	0.29	2.5
1996	48	0.35	217	0.24	2.1	20	0.35	278	0.24	2.0
1997	62	0.35	398	0.20	1.9	23	0.17	889	0.21	1.9
1998	73	0.44	504	0.12	1.6	45	0.40	703	0.12	1.6
1999	84	0.42	553	0.08	1.6	43	0.40	761	0.06	1.5
2000	114	0.40	607	0.10	1.7	57	0.42	974	0.10	1.6
2001	56	0.34	454	0.17	2.0	29	0.34	602	0.16	1.9
2002	43	0.33	343	0.17	1.8	21	0.33	375	0.15	1.6
2003	38	0.37	394	0.15	1.7	16	0.31	717	0.18	1.8
2004	45	0.33	621	0.12	1.6	23	0.17	1056	0.13	1.7
2005	42	0.14	897	0.14	1.8	32	0.13	1085	0.15	1.9
2006	37	0.16	1010	0.11	1.7	23	0.09	1435	0.10	1.8
2007	23	0.09	480	0.16	2.1	9	0.11	825	0.15	2.2
2008	25	0.24	500	0.18	2.0	11	0.18	794	0.16	2.0
2009	3	-	1017	0.10	1.5	2	-	809	0.12	1.7
2010	3	0.33	148	0.14	2.5	2	-	210	0.09	2.8
2011	3	0.33	306	0.01	1.2	3	0.33	306	0.01	1.2
2012	5	0.20	632	0.10	1.3	2	-	1418	-0.03	0.9

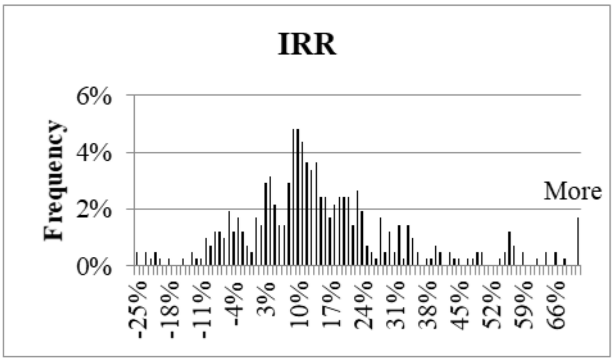
Appendix 3: Histograms

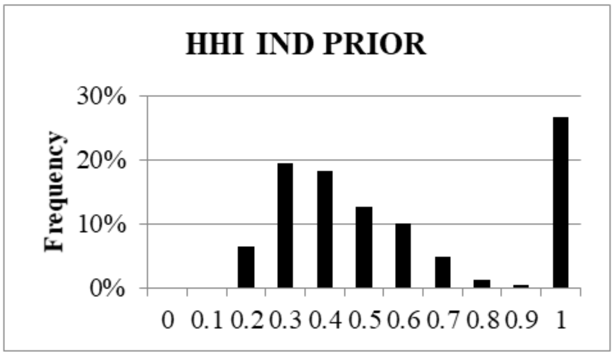
The following histograms depict Sample B's variable distribution. The first histogram details the distribution of FIRM AGE, from 1 to 20 and "more". The second histogram details the distribution of FUND SEQUENCE, from 1 to 15 and "more". The third histogram details the distribution of MOIC, from 0 to 5 and "more". The fourth histogram details the distribution of IRR, from -25% to 70% and "more". The fifth histogram details the distribution of HHI IND PRIOR, from 0 to 1. The sixth histogram details the distribution of HHI GEO PRIOR, from 0 to 1. The seventh histogram details the distribution of DEALS PRIOR, from 1 to 25 and "more".

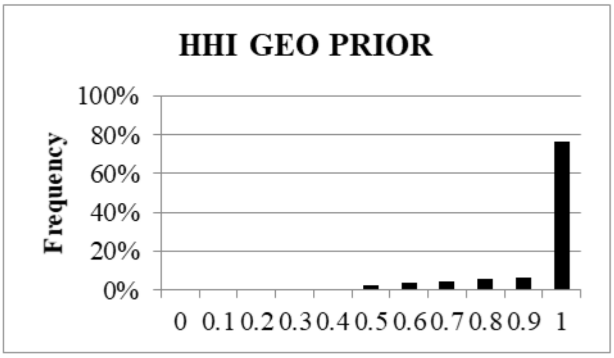












Appendix 4: Correlation Matrix

The following table shows the Pearson Correlation Coefficients among the dependent (MOIC, IRR), independent (FUND SEQUENCE, FIRM AGE, DEALS PRIOR, HHI IND PRIOR, HHI GEO PRIOR), and control (FUND SIZE) variables for the Samples A and B. Both rows and columns list those variable in the same order. The sample Size of Sample A is 903 and that of Sample B is 413. The asterisk indicates the statistical significance level of 1%.

Sample A	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
(1) MOIC	1.00					
(2) IRR	0.78*	1.00				
(3) FUND SIZE	0.05	-0.04	1.00			
(4) FUND SEQUENCE	0.02	0.04	0.48*	1.00		
(5) FIRM AGE	0.03	0.02	0.44*	0.84*	1.00	
(6) DEALS PRIOR	0.02	-0.01	0.35*	0.48*	0.47*	1.00

n = 903; * indicates 1% significance level

Sample B	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
(1) MOIC	1.00							
(2) IRR	0.79*	1.00						
(3) FUND SIZE	0.04	0.04	1.00					
(4) FUND SEQUENCE	0.08	0.13	0.41*	1.00				
(5) FIRM AGE	0.11	0.10	0.36*	0.72*	1.00			
(6) DEALS PRIOR	0.00	0.01	0.25*	0.26*	0.19*	1.00		
(7) HHI IND PRIOR	-0.07	0.07	-0.26*	-0.12	-0.14	-0.38*	1.00	
(8) HHI GEO PRIOR	0.05	0.04	-0.34*	-0.15*	-0.11	-0.28*	0.26*	1.00

n = 413; * indicates 1% significance level

Appendix 5: Test for Multicollinearity

The table shows the Variance Inflation Factors (VIFs) for our two main regression models from Table 6. The VIF detects multicollinearity in regression models by measuring how much the variance of an independent variable is influenced by its correlation with the other independent variables. According to Woolridge (2016), a general rule is that a VIF greater than 10 suggests multicollinearity. Except for log(FUND SIZE) and log(FUND SIZE)^2 all independent variables in our models are below this threshold. Due to the definition and calculation of log(FUND SIZE) and log(FUND SIZE)^2 their high values are logical and do not present an issue.

Variables	Sample A	Sample B
FIRM AGE	4.81	2.44
FUND SEQUENCE	3.68	2.50
DEALS PRIOR	1.57	1.79
*DEALS PRIOR * FIRST QUARTILE PRIOR*		2.14
HHI GEO PRIOR		1.35
HHI IND PRIOR		1.70
log(FUND SIZE)	33.27	45.23
log(FUND SIZE)^2	33.61	46.86
VC DUMMY	1.31	1.57
FIRST QUARTILE PRIOR	3.17	3.34
SECOND QUARTILE PRIOR	3.19	2.77
THIRD QUARTILE PRIOR	2.59	2.38
NA QUARTILE PRIOR	6.31	1.22
REGION FIXED EFFECTS	1.13	3.19
TIME FIXED EFFECTS	1.72	2.14

Appendix 6: Regression Output with Dependent Variables in Natural Logarithm

The table shows the OLS regression output of our robustness test with the dependent variables MOIC and IRR in the natural logarithm (IRR is transformed into log(1+IRR)). The data samples applied are the same as in the main regression table, Sample A with 903 PE funds and Sample B with 413 PE funds. To proxy experience we use the five independent variables FIRM AGE, FUND SEQUENCE, DEALS PRIOR, HHI GEO PRIOR, and HHI IND PRIOR as well as an interaction term of DEALS PRIOR and FIRST QUARTILE PRIOR. In addition, we control for a range of other variables that may affect performance: the natural logarithm of FUND SIZE and of FUND SIZE^2, the investment strategy (VC DUMMY) and the prior fund's quartile. All regressions include Region and Time Fixed Effects. Standard errors are adjusted for heteroskedasticity.

	Sample A		**Sample B**	
Variables	**(5) log(MOIC)**	**(6) log(1+IRR)**	**(7) log(MOIC)**	**(8) log(1+IRR)**
FIRM AGE	0.02***	0.00	0.01**	0.00
	(0.01)	(0.00)	(0.01)	(0.00)
FUND SEQUENCE	-0.01	0.00	-0.01	0.00
	(0.01)	(0.00)	(0.01)	(0.00)
DEALS PRIOR	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
*DEALS PRIOR * FIRST QUARTILE PRIOR*			-0.01*	-0.00
			(0.00)	(0.00)
HHI GEO PRIOR			0.08	0.02
			(0.18)	(0.05)
HHI IND PRIOR			-0.15	-0.03
			(0.12)	(0.03)
log(FUND SIZE)	-0.04	0.01	-0.14	0.02
	(0.09)	(0.02)	(0.12)	(0.03)
log(FUND SIZE)^2	0.00	-0.00	0.01	-0.00
	(0.01)	(0.00)	(0.01)	(0.00)
VC DUMMY	-0.35***	-0.08***	-0.32***	-0.06***
	(0.05)	(0.01)	(0.09)	(0.02)
FIRST QUARTILE PRIOR	0.40***	0.10***	0.47***	0.11***
	(0.09)	(0.03)	(0.10)	(0.03)
SECOND QUARTILE PRIOR	0.24***	0.05**	0.26***	0.05**
	(0.09)	(0.02)	(0.09)	(0.03)
THIRD QUARTILE PRIOR	0.20**	0.03	0.22**	0.03
	(0.09)	(0.03)	(0.10)	(0.03)
NA QUARTILE PRIOR	0.29***	0.07***		
	(0.09)	(0.03)		
CONSTANT	1.16***	0.14*	1.25***	0.20*
	(0.25)	(0.08)	(0.44)	(0.12)
Observations	903	903	413	413
Time fixed effects	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES
Adjusted R-squared	0.17	0.14	0.22	0.20

*, **, *** indicate 10%, 5% and 1% significance level, respectively.
Standard errors are in parentheses and are adjusted for heteroskedasticity.

Appendix 7: Regression Output without Firm Age

The table shows the OLS regression output of our robustness test dropping the variable FIRM AGE from the models. The data samples applied are the same as in the main regression table, Sample A with 903 PE funds and Sample B with 413 PE funds. The dependent variables in our models are MOIC and IRR. To proxy experience we use the four independent variables FUND SEQUENCE, DEALS PRIOR, HHI GEO PRIOR, and HHI IND PRIOR as well as an interaction term of DEALS PRIOR and FIRST QUARTILE PRIOR. In addition, we control for a range of other variables that may affect performance: the natural logarithm of FUND SIZE and of FUND SIZE^2, the investment strategy (VC DUMMY) and the prior fund's quartile. All regressions include Region and Time Fixed Effects. Standard errors are adjusted for heteroskedasticity.

	Sample A		Sample B	
Variables	**(9) MOIC**	**(10) IRR**	**(11) MOIC**	**(12) IRR**
FUND SEQUENCE	0.03*	0.01***	0.02	0.01**
	(0.01)	(0.00)	(0.02)	(0.00)
DEALS PRIOR	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
*DEALS PRIOR * FIRST QUARTILE PRIOR*			-0.01**	-0.00
			(0.01)	(0.00)
HHI GEO PRIOR			0.01	0.01
			(0.28)	(0.06)
HHI IND PRIOR			-0.45**	-0.04
			(0.21)	(0.04)
log(FUND SIZE)	-0.15	0.01	-0.14	0.03
	(0.16)	(0.03)	(0.23)	(0.04)
log(FUND SIZE)^2	0.00	-0.00	0.00	-0.00
	(0.01)	(0.00)	(0.02)	(0.00)
VC DUMMY	-0.41***	-0.08***	-0.21	-0.06*
	(0.10)	(0.16)	(0.18)	(0.03)
FIRST QUARTILE PRIOR	0.61***	0.12***	0.72***	0.13***
	(0.17)	(0.03)	(0.19)	(0.03)
SECOND QUARTILE PRIOR	0.28*	0.04	0.27	0.04
	(0.15)	(0.03)	(0.18)	(0.03)
THIRD QUARTILE PRIOR	0.20	0.02	0.28	0.03
	(0.16)	(0.03)	(0.18)	(0.03)
NA QUARTILE PRIOR	0.23	0.07**		
	(0.14)	(0.03)		
CONSTANT	3.34***	0.16*	3.48***	0.24*
	(0.44)	(0.09)	(0.77)	(0.14)
Observations	903	903	413	413
Time fixed effects	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES
Adjusted R-squared	0.15	0.13	0.21	0.18

*, **, *** indicate 10%, 5% and 1% significance level, respectively.

Standard errors are in parentheses and are adjusted for heteroskedasticity.

Appendix 8: Robustness Checks for Industry Prior and Interaction Term

The table shows the OLS regression output of our robustness test regarding the Herfindahl-Hirschman Index and the Interaction Term of DEALS PRIOR and FIRST QUARTILE PRIOR. The data sample applied is only Sample B with 413 PE funds. In the regressions (13) and (14), we replace the Herfindahl-Hirschman Index variables by variables counting the total number of geographies (GEO COUNT PRIOR) and industries (IND COUNT PRIOR) a prior fund invested in. In regressions (15) and (16), we use the HHI variables but add a SPECIALIST DUMMY to control for the effect of fund specialisation in the current fund. In regressions (17) and (18), we run our main model and additionally include the variable DEALS to control for the number of deals in the current fund. Regression (13) and (14) operate on Sample B. Regression (15) to (18) run on a reduced sample of 387 funds for which current data on the number of deals, geographies and industries invested in are available. All regressions include Region and Time Fixed Effects. Standard errors are adjusted for heteroskedasticity.

	Sample B		**Sample B (reduced)**		**Sample B (reduced)**	
Variables	**(13) MOIC**	**(14) IRR**	**(15) MOIC**	**(16) IRR**	**(17) MOIC**	**(18) IRR**
FIRM AGE	0.02**	0.00	0.02*	0.00	0.02*	0.00
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
FUND SEQUENCE	-0.01	0.00	-0.01	0.00	-0.00	0.00
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
DEALS PRIOR	-0.00	0.00	-0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
*DEALS PRIOR * FIRST QUARTILE PRIOR*	-0.02**	-0.00	-0.01**	-0.00	-0.01**	-0.00
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
GEO COUNT PRIOR	0.03	0.01				
	(0.07)	(0.01)				
IND COUNT PRIOR	0.08**	-0.01				
	(0.04)	(0.01)				
HHI GEO PRIOR			0.03	0.01	-0.05	-0.00
			(0.28)	(0.06)	(0.28)	(0.06)
HHI IND PRIOR			-0.31	-0.03	-0.28	-0.02
			(0.23)	(0.04)	(0.21)	(0.04)
SPECIALIST DUMMY			0.11	0.05		
			(0.22)	(0.04)		
DEALS					-0.00	-0.00**
					(0.00)	(0.00)
log(FUND SIZE)	-0.13	0.04	-0.3	-0.01	-0.31	-0.02
	(0.23)	(0.04)	(0.27)	(0.05)	(0.27)	(0.05)
log(FUND SIZE)^2	0.00	-0.00	0.02	-0.00	0.02	0.00
	(0.01)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
VC DUMMY	-0.21	-0.06*	-0.20	-0.06**	-0.13	-0.04
	(0.18)	(0.03)	(0.18)	(0.03)	(0.20)	(0.03)
FIRST QUARTILE PRIOR	0.71***	0.13***	0.64***	0.12***	0.63***	0.12***
	(0.19)	(0.03)	(0.20)	(0.04)	(0.20)	(0.04)
SECOND QUARTILE PRIOR	0.24	0.04	0.22	0.04	0.23	0.04
	(0.18)	(0.03)	(0.18)	(0.03)	(0.18)	(0.03)
THIRD QUARTILE PRIOR	0.27	0.03	0.20	0.02	0.22	0.02
	(0.17)	(0.03)	(0.19)	(0.03)	(0.18)	(0.03)
CONSTANT	3.07***	0.20	4.17***	0.40**	4.18***	0.40**
	(0.71)	(0.13)	(0.86)	(0.17)	(0.17)	(0.17)
Observations	413	413	387	387	387	387
Time fixed effects	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.22	0.18	0.22	0.19	0.22	0.20

*, **, *** indicate 10%, 5% and 1% significance level, respectively.
Standard errors are in parentheses and are adjusted for heteroskedasticity.