ESSAYS IN PRIVATE EQUITY

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ABSTRACT

The private equity industry has witnessed significant growth during the last two decades, fuelled by the increasing demand by institutional investors. Meanwhile, as the industry matured and competition among fund managers increased, attractive early returns disappeared, and performance persistence diminished, increasing the difficulty of private equity fund manager selection. Moreover, fund managers are better informed about their own quality compared to the potential investors, which constitutes an information asymmetry and exacerbates the difficulty of finding the right fund manager.

This thesis explores the information asymmetry in the private equity industry and its effects on investor behaviour. Chapter 1 evaluates several ways public pension funds ("PPF") deal with this information asymmetry. I show that fund selections driven by specialist investment consultants overperform. PPFs with experienced trustees need less support from consultants and perform better in internally-driven fund manager selections. Additionally, investors exhibit herd behaviour in their fund manager selection. A strong informational signal by a PPF about a PE fund attracts others to invest in the same fund. Herd behaviour increases under lower information availability and when the source of the informational signal is a more credible PPF.

In Chapter 2, we challenge the use of the internal rate of return ("IRR") as the main performance measurement tool for private equity funds, and we demonstrate that the IRR is affected by two biases: a convexity bias, and a "quit-whilst-ahead" bias arising because the returns on PE projects tend to covary with their durations. Using a range of parametric and non-parametric estimation techniques, we show that these biases boost fund IRRs by an average of around 3% per annum - a significant proportion of the average net PE fund IRR (around 12% per annum). These results suggest that IRRs misguide investors during the asset allocation and fund selection processes.

In Chapter 3, I assess the quality of the information provided by the fund managers to their investors. I show that adopting fair value accounting increases the accuracy of the interim fund valuations of buyout funds significantly. This increase is accompanied by the increased valuation effort of the private equity funds and is robust to the possible confounding effects of the global financial crisis. Beneficial effects of local fair value measurement standards spill over to other geographies, mainly due to the peer pressure effect. Fair value measurement eliminates the significant heterogeneity in valuation quality from the difference in fund investor profiles.

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Chapter 1

In Pursuit Of Information: Information Asymmetry in Private Equity Commitments

Abstract

Private Equity ("PE") investors are exposed to asymmetric information during their fund manager selection process. This paper evaluates several ways public pension funds ("PPF"), the largest capital provider to PE funds, deal with this information asymmetry. Fund selections driven by specialist investment consultants overperform. PPFs with specialist consultants are more willing to invest in PE funds with limited available information, and they achieve better investment performance. PPFs with experienced trustees need less support from consultants and perform better in internally-driven fund manager selections. Additionally, investors exhibit herd behaviour in their fund manager selection. A strong informational signal by a PPF about a PE fund attracts others to invest in the same fund. Herd behaviour increases under lower information availability and when the source of the informational signal is a more credible PPF.

1.1 Introduction

Institutional investors perform private equity ("PE") investments dominantly through PE funds. Experienced PE firms collaborate with the investors to form these funds, in which they act as the fund managers and have complete authority regarding investment-related decisions, while the responsibility of the investors is limited to providing the committed capital. In this structure, PE investment performance of an investor is merely determined by their success in fund selection.

However, PE fund selection process is riddled with asymmetric information between the fund investor and the fund manager. PE has a shorter history compared to other traditional asset classes, and it is difficult for investors to assess the expected performance of fund managers that does not have a long track record. Moreover, even an adequately long and successful track record does not necessarily help since performance persistence significantly decreased during the last two decades as the industry became more competitive. (Sensoy, Wang, Weisbach, 2014; Braun, Jenkinson, Stoff, 2017).

Additionally, several unique characteristics of the PE industry amplify the asymmetric information problem faced by fund investors and emphasize the importance of working with the right fund managers. First, investments in PE funds are illiquid, and the secondary market is shallow, which means that the capital injected into the fund by the investors will be locked for years in investments solely decided and managed by the fund manager. Second, the fees paid to PE firms are high, and the fee structures are opaque. Finally, given the absence of a regular market valuation of the fund assets, measuring the risk-adjusted performance of a private equity fund is almost impossible. Internal Rate of Return, the performance metric that is dominantly used by the PE industry to assess fund performance, is shown to be biased and can be misleading (Phalippou and Gottschalg, 2009; Hayley and Sefiloglu, 2022). All of these factors make it crucial for investors to have access to high-quality information on PE funds, to make better-informed investment decisions.

This paper aims to deepen our understanding of how institutional investors deal with the information asymmetry in the fund selection process by focusing on a specific investor type, public pension funds ("PPF"). I explore the following three related research questions by evaluating investment consultants, trustee experience and peers' actions as three information sources: First, do investment consultants create value for PPFs in their PE fund selection process? Second, how does the experience of PPF trustees affect the use of consultants and fund selection performance? And third, do PPFs use peers' investments as an information signal (i.e. herding)?

Understanding how PPFs decide which PE funds to invest in is important. To begin with, PPFs in the United States manage \$4.8 trillion for public pensioners, who rely on the pension payment they are promised to receive during their retirement. However, the financial health of these institutions significantly deteriorated during the last 20 years. As of 2019, the average funding ratio of the PPFs in the United States is slightly above 70%, highlighting a funding deficit of \$1 trillion, which constitutes a significant risk to the financial well-being of taxpayers. Moreover, with gradually increasing asset allocation to PE investments during the last two decades, PPFs provide more than 20% of the yearly PE fundraising, making them the largest group of PE investors. However, academic findings on PPF performance in their PE investments are not encouraging, showing an underperformance against most other institutional investor groups (Lerner, Schoar and Wongsunwai, 2007; Hochberg and Rauh, 2013). Moreover, since investment returns represent 61% of total PPF revenues (National Association of State Retirement Administrators, 2021b), gaining a deeper insight into their PE investment decision-making processes is crucial.

The first part of the paper focuses on how PPFs use investment consultants to overcome informational disadvantages. PPFs employ investment consultants to receive assistance in various aspects of the investment management process. General investment consultants are typically mandated to assist the PPF board in determining the asset allocation and the overall investment strategy. Some PPFs also employ a specialist consultant with extensive PE industry knowledge, experience and network and give them the responsibility to build a short-list of potential PE funds to invest in, perform due diligence, or even choose the funds to be invested in. To distinguish between PE fund selections that are driven by the consultants from the ones that are initiated by the internal PPF teams, I build a proxy which highlights the fund selections that a PPF does along with other clients of the same consultant. To confirm the reliability of this proxy variable, I show that the highlighted fund selections are more likely to be driven by the consultant since these fund firms are more likely to have past relationships with the consultant and less with the PPF, and these funds are more likely to have a PE strategy matching the consultant's preference. Using this proxy variable, I show that PE fund selections driven by consultants perform better, and this over-performance is owed exclusively to the specialist consultants, which represent access to high-quality information. These results show that better information access matters significantly for a PE investor. In the next step, I show that specialist consultants provide better fund access; they lead PPFs into investments in high-risk strategies and unrelated fund firms. Overall, by working with PE-specialist investment consultants, PPFs alleviate their informational disadvantages, extend their investment horizon to new strategies and PE fund firms, and end up with better investment performance.

Next, I evaluate the role of trustee experience in the fund selection process. PPFs are managed by a Board of Trustees, which takes investment-related decisions with the assistance of the consultants, the investment committee and the internal investment team. PPF trustees can be selected from various state offices, they may be plan members, or they can be chosen among the members of the public, and their asset management and finance-related experience vary significantly depending on their background and the way they are selected for the post. I show that boards with less experienced trustees rely more on investment consultants during their fund selection process. Additionally, these PPFs perform worse in internally driven PE fund selections. These results show that PPFs with less related experience suffer more from the adverse effects of information asymmetry, and these PPFs seek more guidance to overcome these effects.

Finally, the last section of the paper focuses on how the PPFs use informational signals from peers in their investment decisions. Fund firms' commitment collection process for their new funds may last for a few years, allowing the investors to observe the investment decisions of others regarding the same PE fund and adjust their decisions accordingly. Using the data on the commitment dates of each investor to PE funds, I show that PPFs herd in their PE fund commitment decisions. An abnormally high amount of commitment in a PE fund by a peer constitutes a strong informational signal, leading to a higher amount of total commitments by other PPFs. The importance attributed to these signals increases when the information asymmetry is severe, such as investments in riskier strategies and fund firms without prior experience, and when the signal belongs to a more credible investor, which is proxied by PPF size and experience in PE investments.

This paper contributes to several strands of academic literature, including private equity investments of institutional investors (Lerner, Schoar and Wongsunwai, 2007; Sensoy, Wang and Weisbach, 2014) and their fund selection practices (Fried, Hisrich, 1992; Gompers, Lerner and Blair, 1998; Barnes, Menzies, 2005; Lerner, Schoar and Wongsunwai, 2007; Groh and Liechtenstein, 2011; Azzi and Suchard, 2019; Barber, Morse and Yasuda, 2021; Goyal, Wahal and Yavuz, 2021) by extending our knowledge on the private equity investment practices of a specific type of institutional investor, public pension funds.

Moreover, this paper documents herd behaviour in the private equity industry; thus, it contributes to the empirical literature on herd behaviour in financial markets (Lakonishok, Shleifer and Vishny, 1992; Christie, Huang, 1995; Wermers, 1999; Sias, 2004; Blake, Sarno and Zinna, 2017; Goyal, Wahal and Yavuz, 2021). The paper provides insights into the herd behaviour for a new asset class with a new methodology that assesses the influence of peers' actions on investment decisions.

Finally, the paper contributes to the academic literature on pension fund governance (Andonov, Hochberg and Rauh, 2018; Hochberg and Rauh, 2013; Morkoetter and Schori, 2021) by discussing the effects of the board of trustee composition on investment processes and fund selection performance.

1.2 Background & Literature Review

1.2.1 Private Equity Industry, Fund Selection & Information Asymmetry

A PE fund is a partnership of fund investors called limited partners ("LP"), which are mostly large institutions (e.g. pension funds, university endowments, banks, insurance companies), and fund managers called general partners ("GP") that are experienced asset management houses that specialize in the acquisition of and value creation from private companies (e.g. KKR, Carlyle, Apollo, Blackstone). A typical PE fund is a closed-end fund with a pre-determined life (10 years is the industry norm), it is invested by a few to a few dozen investors, and it is dissolved after all of the fund's investments are liquidated, and proceeds are distributed back to the investors.

PE has been wildly popular among institutional investors over the last few decades. PE fundraising increased from $110bn to $1.1trn between 2003 and 2019 (McKinsey, 2020). Assessing PE performance is difficult since there is limited room to apply factor models and calculate risk-adjusted returns due to the lack of active market valuations, which resulted in a heated academic debate on whether PE over-perform the public equity, but the investor perception has been positive on the performance of this asset class. Moreover, PE investments are widely believed to provide significant diversification benefits since they have low correlations with public market returns, although this belief is academically challenged from different angles (Franzoni, Nowak and Phalippou, 2012; Welch and Stubben, 2018).

Although the term "Private Equity" is sometimes used with its narrow definition to represent only Buyout funds, the variety of sub-strategies and the investment complexity within this umbrella term grew dramatically over time. Figure 1 presents how the PE industry evolved in terms of the shares of the sub-strategies considered to be a part of this industry. At the beginning of the 2000s, the PE industry consisted solely of "Buyout" and "Venture Capital" funds and "Funds-of-Funds" investing in them. Buyout funds invest in mature private companies with room for operational and financial efficiency improvement. Venture Capital funds provide capital to start-ups and early-stage companies with high potential and a high risk of failure. In time, "Debt", "Real Estate", and "Real Asset" strategies flourished. Debt funds provide different types of debt financing to private firms, with varying risks and returns. "Real Asset" funds invest in commodities and infrastructure projects, while "Real Estate" funds invest in real estate projects for a steady cash stream. Overall, the PE industry became much more complex over time, dramatically increasing the need for better information and the level of expertise required to succeed.

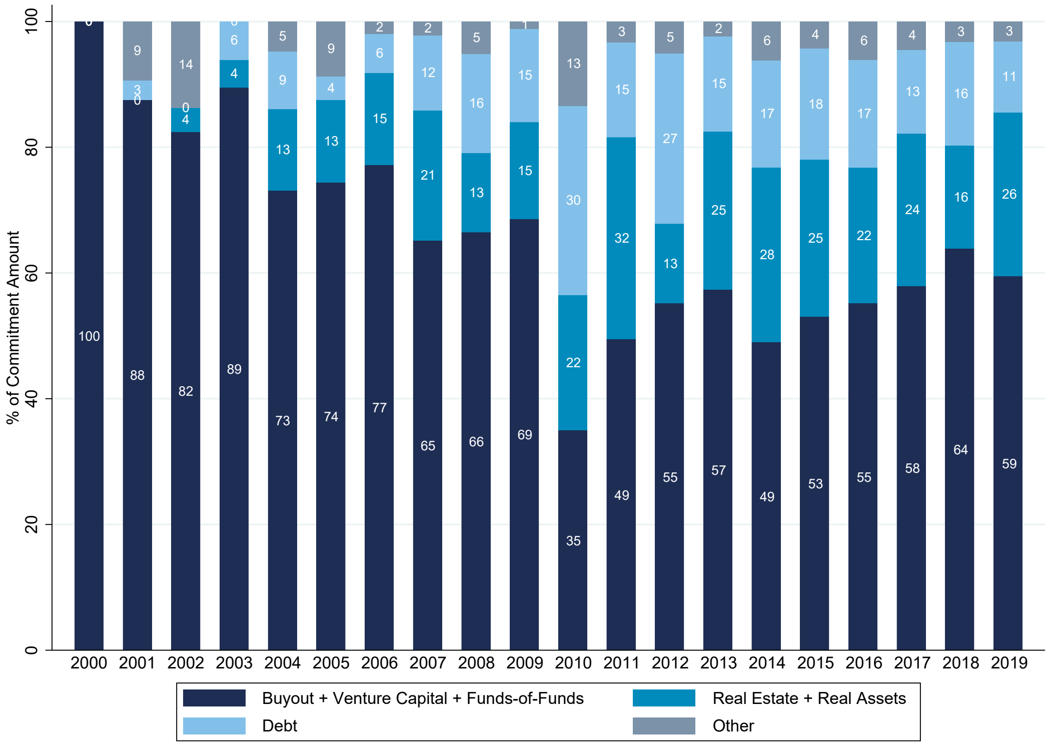

Figure 1.1: Private Equity Fund Strategy Breakdown per Vintage

This figure presents the yearly evolution of the private equity industry, in terms of the % of commitments made in each strategy group. Buyout, Venture Capital and Fund-of-Funds represent the core private equity strategies. Buyout funds invest in mature private companies with room for operational and financial efficiency improvement. Venture Capital funds provide capital to start-ups and early-stage companies with high potential and a high risk of failure. "Real Asset" funds invest in commodities and infrastructure projects, while "Real Estate" funds invest in real estate projects for a steady cash stream. "Debt" funds provide different types of debt financing to private firms, with varying risks and returns. "Other" category includes co-investment and secondaries funds.

Several unique attributes of the PE industry compound the importance of access to better information on the potential fund managers for the investors. First, performance measurement is very difficult in PE. Investments do not have market valuations, and their final values can only be perfectly uncovered after they are fully liquidated. Interim valuations of fund managers are mostly unreliable (Jenkinson, Sousa, Stucke, 2013; Brown, Gredil, Kaplan, 2019), which makes it impossible to calculate the risk-adjusted performance of individual PE funds. As a result, the Internal Rate of Return ("IRR") prevails as the leading performance metric despite being open to manipulations. Additionally, performance persistence is shown to have diminished as the PE industry matured (Braun, Jenkinson and Stoff, 2017). Therefore, it is very difficult to adequately evaluate the past and estimate the future performance of the fund managers.

Moreover, PE investments are very illiquid. Based on the closed-end fund structure that the PE industry relies on, general partners decide when the committed capital will be called and when it will be paid back, and the investors have no right to ask for early payment. Although the average holding period for buyout investments is around four years (Braun, Jenkinson and Stoff, 2017), academic literature provides evidence that best-performing deals are exited early. In contrast, the worst performers are held for a long time (Hayley and Sefiloglu, 2022), meaning that fund investors can end up waiting for a decade to receive a part of their investment back.

Finally, the opaqueness of the fund manager fee structure and the complexity of fee calculations have been a significant struggle for PE investors. On top of the traditional 2/20 structure, in which a management fee of 2% per annum and carried interest of 20% for the returns exceeding the pre-determined hurdle rate is paid to fund managers, investors face additional transaction and monitoring fees, which are not necessarily transparent enough (Phalippou, Rauch, Umber, 2018). Working with a new fund manager brings the risk of being exposed to additional fees hidden in the complexity of limited partnership agreement documents.

The academic literature provides limited insight into institutional investors' PE fund selection practices and the asymmetric information problem contaminating the fund selection process. A set of papers perform interviews with investors to deepen our understanding of what factors affect their decision to choose a PE fund. Fried and Hisrich (1992) highlight the importance of GP experience in the fund selection decision. Out of 18 investors interviewed within the scope of the paper, only 2 express an interest in investing in a fund of a general partner without venture capital industry experience. The paper also underlines the difficulties related to performance measurement in the PE industry, given that the interim calculations based on NAVs calculated by the fund manager are misleading. Some investors refuse to consider investing in a fund of a general partner which does not have a fully-liquidated prior fund. Barnes and Menzies (2005) discuss the importance of general partner reputation and track record in fund selection. Investors interviewed for both papers also emphasize the importance of going beyond the numbers while screening the potential PE funds to invest, stating that they communicate with many other LPs, entrepreneurs and fund managers to collect information about the PE fund of interest. Finally, Groh and Liechtenstein (2011) also quote track record, local market experience, and team members' reputation as important fund sorting criteria for PE investors. Overall, these papers underline the need for investors to know more about a potential fund manager before investing in their fund.

Azzi and Suchard (2019) focus on the Chinese PE market, characterized by information asymmetry compounded by regulatory uncertainties and legal difficulties. The paper shows that foreign investors deal with information asymmetry by investing in larger funds of more experienced fund firms that are not affiliated with the Chinese government. The paper also shows that PE funds backed by foreign investors underperform compared to the ones backed by domestic investors, highlighting the importance of information access in the PE industry.

Another strand of academic literature evaluates the tendency of investors to prefer geographically closer PE funds over others. Morkoetter and Schori (2021) show that investors prefer PE funds located in the same geographical region, and under high information asymmetry (proxied by fund sequence and fund manager age), these investments overperform the ones that are in other geographic regions. Hochberg and Rauh (2013) approach a similar question from a political perspective, assessing how political impacts affect fund selection decisions. The paper shows that investors overweight their PE investments in home-state PE funds, and this overallocation is substantially higher for PPFs. The paper argues that the likely reasons for this behaviour are political pressures and the lack of resources to adequately screen the funds that are not local. In a related study, Andonov, Hochberg and Rauh (2018) show that politically affiliated boards are more likely to invest in PE funds that other investors neglect.

Finally, Goyal, Wahal and Yavuz (2021) explore private equity fund selection criteria and show that young GPs without a track record are more likely to be selected by the LPs, and this observation coincides with the increased allocation to PE.

1.2.2 Public Pension Funds & Role of Investment Consultants

The central or state governments administer PPFs to provide financial security to the participants during their retirements. Under the "Defined Benefit" plan structure, which is the dominant structure for PPFs and the subject of this study, the employee (plan participant) and the employer (plan sponsor) provide regular contributions to the fund during employment, and the fund is obliged to fulfil the pre-determined contractual liabilities to employees following their retirement. These liabilities are independent of the financial situation and the funding status of the PPF.

Future obligations to plan participants significantly exceed the contributions collected during their employment for the defined benefit plans. For the collected contributions to cover the long-term liabilities, pension funds need to ensure that pension assets earn a decent annual return within a long-term focused investment strategy. According to the National Association of State Retirement Administrators (2021b), investment returns account for 61% of the PPF revenues, whereas employer and employee contributions only account for the remaining 39%. The absence of healthy returns on assets creates a gap between the fund assets and liabilities, decreasing the funding ratio and creating a significant risk for the plan subscribers. Especially after the global financial crisis of 2008 - 2009, public pension funds witnessed a dramatic deterioration in their funding ratios which decreased to 72.4% as of 2019 from 101.9 % in 2001 (Public Plans Data, 2021).

As of September 2020, PPFs in the United States control assets amounting to $4.8 trillion (National Association of State Retirement Administrators, 2021a). Since the interest rates have been close to zero for more than a decade now, and the equity returns are much lower compared to the previous decades, pension funds have been looking for alternative investment opportunities that can provide them with the required returns for the fund assets to catch-up with the growth in liabilities. As a result of the pursuit of higher returns, PPFs shifted their attention towards alternative investments. From 2001 to 2019, allocations to private equity by public pension funds in the United States increased from 3.6% to 9.1% (Public Plans Data, 2021). Figure 2 depicts the evolution of yearly PE commitments by PPFs. Apart from a temporary setback during the financial crisis, it can be observed that yearly commitments increased at a fast pace during the last two decades.

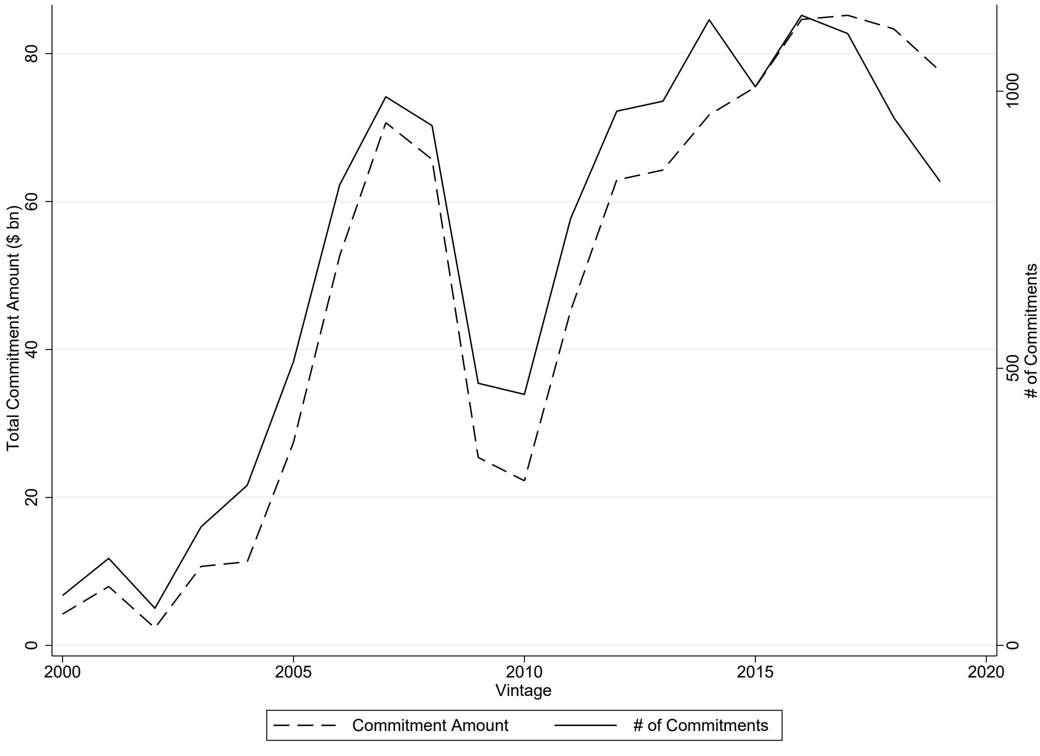

Figure 1.2: Private Equity Commitments of Public Pension Funds

This figure presents the yearly evolution of the total number (right axis) and amount (left axis) of private equity commitments made by the US public pension funds.

Figure 3 goes one step further and presents the percentage of yearly PE fundraising satisfied by PPF commitments. We observe that the significance of PPFs as institutional PE investors increased in time, with the percentage of PPF commitments exceeding 20% of total PE fundraising. With these shares of total commitments within the industry fundraising, PPFs stand out as the largest group of institutional PE investors.

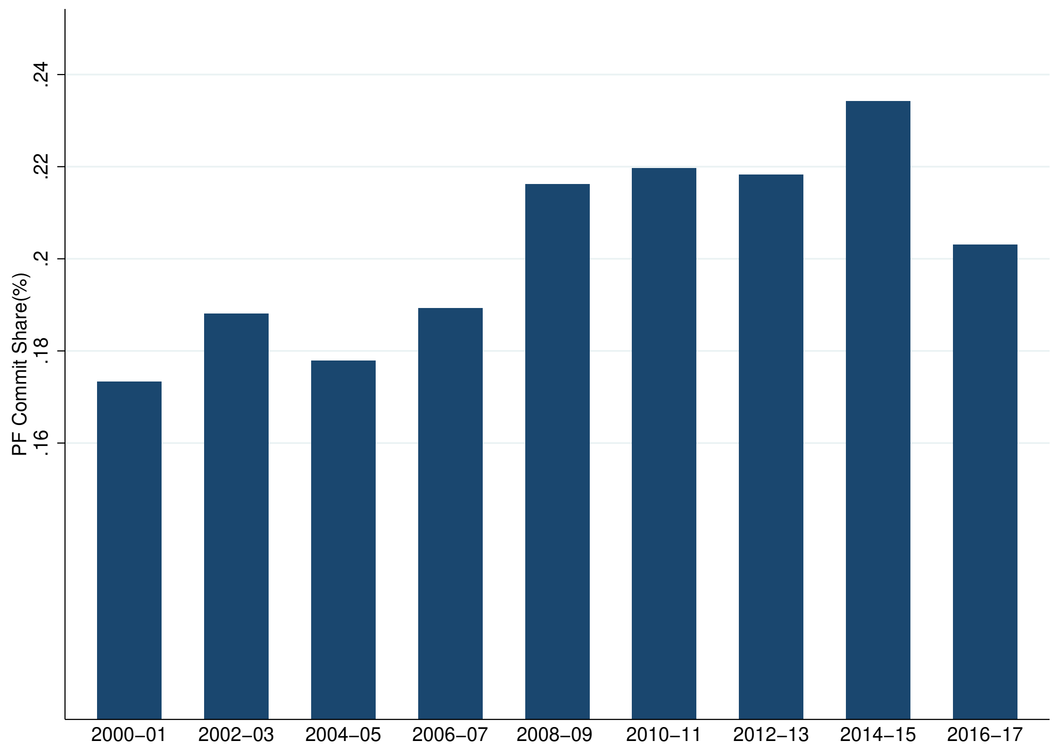

Figure 1.3: US Public Pension Fund Ownership of Private Equity Funds

This figure presents the evolution of the average ownership of private equity funds by the US public pension funds.

PPFs are managed by a "Board of Trustees", which is responsible for acting as the fiduciary of plan participants. Trustees determine the investment asset allocations and work with the internal teams to determine the asset managers to be mandated for the allocated funds to be managed. With the help of the professional investment staff and consultants, trustees allocate funds to private equity strategies and decide which private equity funds to commit and the amount of these commitments. Although some large pension funds have in-house fund managers for traditional asset classes like public equities and bonds, private equity investments are almost exclusively handled using external managers since they require a high level of specialization (Jung and Rhee, 2013).

Trustee backgrounds can be categorized into three groups. "State" board members hold a government-related post, "Participant" members are current or retired plan participants, and "Public" trustees are members of the general public. A further categorization can be made depending on how these trustees obtain their seats. "Appointed" trustees are selected by a government representative, “Exofficio” members gain their seats through a position they hold, “Elected” members are chosen by plan participants. These two categorizations create nine different types of trustees with significantly varying investment and asset management experience. Andonov, Hochberg and Rauh (2018) document that public-appointed members represent the trustee group with more relevant experience. This group is also more likely to have a relevant educational degree.

Investment consultants are important “gatekeepers” in the PE industry, helping institutional investors seeking funds to invest while providing the fund firms with invaluable access to desperately sought investor assets. Pension funds employ general investment consultants to receive guidance on investment practices, but employing a consultant also provides a shield for fund trustees in case of bad performance (Goyal and Wahal, 2008; Jones and Martinez, 2014). Depending on the scope of the mandate, these firms provide guidance on setting investment objectives, strategic asset allocation, manager selection, monitoring and performance reporting (Day, 2009). On top of the general consultants, some PPFs prefer to employ specialist consultancy firms as Private Equity and/or Real Estate consultants. These specialist firms have particular experience, focus and professional networks related to these asset classes, and they are generally responsible for a focused service, including fund screening, short-listing, due diligence, reporting and even fund selection.

Academic literature has overlooked the role of investment consultants in PE fund selection. Jenkinson, Jones and Martinez (2016) evaluate the consultant recommendations on actively managed equity funds. The paper shows that not only performance-related but also non-performance factors (e.g. decision-making capability, consistent investment philosophy, the effectiveness of presentations) affect consultant recommendations, but they do not find an over-performance for these recommendations.

1.2.3 Informational Herding in Financial Markets

There is a vast academic literature evaluating herd behaviour in financial markets, mainly focusing on the investing activity in traditional markets such as equities and bonds and equity analysts’ forecasts. In informational herding, the agent omits her own beliefs and thoughts and acts according to others’ actions, intending to overcome informational problems (Banerjee, 1992; Welch, 1992; Bikhchandani et al., 1992).

The first strand of academic literature on informational herding focuses on the effect of the characteristics of the invested asset on herd behaviour. These papers test the informational herding hypothesis that smaller, more volatile, less liquid assets are more difficult to assess for investors; therefore, investors tend to follow others’ trades to overcome the information problems. Lakonishok, Shleifer and Vishny (1992) show that pension funds herd more in the trades of small stocks, consistent with the fact that available information is limited for these stocks, and investors are more likely to pay attention to the trades of others in them. Wermers (1999) reaches similar conclusions for mutual funds by finding that herding is more prominent for smaller and growth-oriented funds for which the availability of information is limited. Sias (2004) also finds greater levels of herding for smaller stocks, suggesting that investors infer information from each others' trades. Similarly, Raddatz and Schmukler (2013) find that pension funds herd for investments in riskier assets for which there is limited information. They argue that herding is a mechanism for pension funds to overcome information problems. Cai et al. (2019) evaluate herding behaviour in the corporate bond market and document higher levels of herding for lower-rated, smaller-sized and more illiquid bonds. Overall, academic literature supports the hypothesis that institutional investors use peers' investments as information sources.

The second group of papers evaluate the effects of market conditions on herd behaviour. The hypothesis is that when market uncertainty increases and investor sentiment deteriorates, investors are more eager to herd since the quality of the available information decreases. This question finds its roots in Keynes (1936), in which it is discussed that imitation of other market participants increases during uncertainty. Empirical research, however, ends up with mixed results. Chang, Cheng and Khorana (2000) and Popescu and Xu (2014, 2018) show that fund managers herd more during down markets. Relatedly, Bekiros et al. (2017), Economou et al. (2018), and Duygun et al. (2021) document a positive effect of fear and uncertainty on herding. However, Christie and Huang (1995) and Hwang and Salmon (2004) do not find evidence of herd behaviour during high market volatility and even decreased herding during financial crises.

Goyal, Wahal and Yavuz (2021) discuss the role of peer investments in the private equity fund selection decisions of the investors. The paper shows that investors are 27% more likely to pick a PE fund from a GP that received a commitment from peers before, highlighting herd behaviour in private equity fund selections. Different from them, in this paper, I am able to identify herd behaviour during the fundraising period of a specific PE fund and show how a strong information signal shapes the investment decision of a PE investor.

1.3 Data and Descriptive Statistics

The data on the PE fund commitments of PPFs is obtained from the Bloomberg Professional terminal. The terminal provides this data from several sources. Although it is not a legal requirement, some pension funds prefer to provide full detail of their private equity fund commitments in their comprehensive annual financial reports, which is the primary data source.

Other major sources are the meeting minutes of the board of trustees and the investment committee meetings. Since the private equity commitments require investment committee and board approvals, each commitment is evaluated, and the details are discussed during these meetings. Finally, some of the commitment information is compiled from specialist websites focusing on the private equity industry. The data from the terminal includes details about the private equity commitments, including the commitment year, amount, PE fund name and GP name. The complete dataset, collected as of July 2020, includes 22,814 commitment observations by 365 PPFs, in 6,130 distinct private equity funds managed by 1,767 general partners.

Some necessary data filtering was made in order to obtain the working sample. 4,269 observations with missing crucial information (commitment amount, private equity fund size, general partner information, limited partner information) are eliminated. 148 observations are dropped because they are old and data for those years is sparse (before 1987), or they have very small commitment (below \$ 1mn) or PE fund size (below \$ 10mn). 256 observations belonging to "Pension Benefit Guaranty Corporation" are dropped since, although this institution is classified as a PPF by Bloomberg Professional terminal, it is a pension guarantee mechanism with a completely different nature. Multiple commitments to a single PE fund by a public pension fund are combined, leading the number of observations to decrease by 423. 1,953 observations for private equity funds in which there is only one pension fund as an investor are left out since investor-fund manager relationships for these observations may be related to a different type of fund management arrangement between the parties. Finally, 390 observations belonging to private equity funds with inconsistency between the fund size and the total collected commitments and observations with inconsistent vintage and commitment years are dropped. Following this data filtering, the working sample with 15,375 commitment observations by 253 public pension funds is obtained, which spans the period between 1992 and 2020.

The final sample corresponds to a US PPF commitment of \$1.1 trillion in PE funds. Although presenting a precise calculation on the comprehensiveness of the sample is not possible due to data limitations, making an overall evaluation is still possible by taking into account the two components of data completeness: (1) Percentage of PE funds covered by the sample (2) Completeness of PPF commitments among the covered PE funds. According to Bain & Company (2020), total fundraising by all types of private equity funds between 2003 to 2019 amounts to \$9.6 trillion globally. The working sample contains private equity funds with a total size of \$4.8 trillion for the vintages of the same period, corresponding to a coverage of 50% of private equity funds in terms of size. For the PE funds in the dataset, the sample highlights total ownership of 20% by the public pension funds in the US. Given that all public pension funds account for close to 30% of the private equity fundraising (Meerkaat and Liechtenstein, 2009; Comtois, 2019) and US public pension funds own close to 60% of pension fund assets globally (OECD, 2020), it can be estimated that for the private equity funds covered within the sample, the dataset provides a high level of data completeness.

Other data used in this study comes from several sources. Data on PPF investment consultants are hand-collected from PPF annual reports and websites, and other web sources. Since PPFs change their consultants periodically and the methodology of this paper requires matching yearly commitments to a specific consultant, the data is collected separately for each year in the sample. No data on consultants could be found for a small number of PPFs in the sample. Therefore, these funds were left out of the analyses related to investment consultants. This decision does not have a major impact on any results. Data on the PE fund firm headquarter locations is obtained from the "Private Equity International" website, combined with hand-collected data obtained from PE firms' websites. The data on the board of trustee structure is kindly provided by Aleksandar Andonov. This dataset has been previously used by Andonov, Hochberg and Rauh (2018).

Table 1 describes the data. Panel A presents the summary statistics for the commitment amounts of PPFs in PE funds for different fund strategies. The median (mean) commitment to PE funds is $40 (68.5) million. Around half of the observations belong to buyout, venture capital and growth funds. Buyout funds receive the largest commitments on average, whereas VC & Growth funds receive smaller commitments. We observe a distribution skewed to the right for all groups, stemming from large commitments to mega-funds. Panel B summarizes the share of PPF commitments within the PE industry. Overall, PPFs are responsible for around 24% of the total commitments made to the average PE fund (20% when weighted by PE fund size). PPF interest exists with a similar magnitude in each PE sub-strategy.

Panel C of Table 1 introduces the main variables of interest under five categories, starting with variables related to consultants. "Consultant Commit" is a binary variable built as a proxy to highlight PE commitments that are more probable to be a proposal of the consultants. In the absence of any available data regarding consultant proposals, this proxy is built on the assumption that a commitment made to a PE fund by multiple clients of the same consultant is more likely to be driven by the investment consultant. Therefore, "Consultant Commit" dummy takes the value of 1 when this is the case and 0 otherwise. This proxy's strength and validity are discussed in the next section. In the working sample, 43% of the observations are highlighted to be driven by consultants. "Specialist Consultant" is a binary variable highlighting the observations that happened in a year when the PPF employs a specialist Private Equity/Real Estate consultant. If a PPF employs a PE specialist consultant, that consultant is assumed to be responsible for all sub-strategies. If a PPF employs a Real Estate specialist consultant but not a PE consultant, this consultant is assumed to be responsible only for the Real Estate fund commitments. Close to 59% of the PE commitments are made by PPFs that employ a specialist consultant. "Consultant - GP Experience" is a binary variable that evaluates whether the consultant has a past relationship with the PE firm via other clients. "Consultant - Strategy Focus" variable is the percentage of prior commitments made to the PE strategy of the observation, via all clients of the consultant.

The second group introduces the variables related to the GP and the PE fund. The average PE fund size is \$3.6 billion. 23% of the commitments are made to the first fund of a GP, and 8.5% of them to the funds headquartered in the same state. The average Net IRR of the PE funds is 11.2%, a figure comparable to previously published data on PE performance. For the funds that are not completely liquidated, IRR is calculated by using the net asset value calculated by the fund manager as a final cash flow. In order to limit the effect of these subjective calculations, PE funds with vintages after 2015 are excluded from the analyses based on fund returns. This exclusion has a negative effect on the strength of the obtained results.

The third group is related to the investors. PPFs in the sample have an average (median) AUM of \$56.6 (32.4) billion. However, these figures hide a significant range of AUMs, ranging between \$42 million and \$386 billion. "LP - Strategy Focus" variable measures the percentage of prior PPF commitments of the same LP made to the same PE strategy.

The fourth group introduces the variables that aim to assess the access difficulties to PE funds. Some PE fund firms, especially reputable ones, can attract more interest to their new funds than their planned fund size. These firms generally select their investors based on certain criteria, such as setting a minimum commitment requirement or refusing to accept small investors into their funds. Unfortunately, no data is available regarding the fund firms' acceptance criteria; therefore, I rely on proxies calculated using the commitment data. "Minimum Commitment" calculates the smallest amount of commitment made to a PE fund. "Smallest Investor Size" is the size of the smallest PPF, other than the PPF of observation that made a commitment in the same PE fund.

The final group of variables are related to the board of trustee structure. "Board Size" is the number of trustees in a PPF board. As explained in the previous section, these board members come from different backgrounds. Andonov, Hochberg and Rauh (2018) show that among the trustee categories, "Public - Appointed" trustees have the greatest experience in finance & asset management. Therefore, in the analyses that require a measure for the board of trustee experience, I use the percentage of public-appointed trustees as a proxy.

Panel A: Commitment Amount ($ mn)	N	Mean	Median	SD
By Observations				
Buyout	5,743	83.2	50	106.5
VC & Growth	2,349	44.6	25	60.6
Debt	2,170	70.9	50	81.3
Real Estate	2,489	67.4	50	73.0
Other	2,624	56.8	30	73.1
Total	15,375	68.5	40	87.7
Panel B: Total PF Commit Share (%)	**N**	**Mean**	**Median**	**SD**
By Unique PE Funds				
Buyout	837	0.203	0.180	0.127
VC & Growth	519	0.223	0.197	0.147
Debt	460	0.248	0.218	0.170
Real Estate	483	0.293	0.250	0.192
Other	579	0.246	0.176	0.209
Total	2,878	0.237	0.200	0.170
Panel C: Variables of Interest	**N**	**Mean**	**Median**	**SD**
1. Consultant Variables				
Consultant Commit (B)	14,061	0.427	0.000	0.495
Specialist Consultant (B)	14,061	0.592	1.000	0.491
Consultant GP Exp (B)	14,061	0.423	0.000	0.494
Consultant Str Focus (%)	13,362	0.305	0.207	0.289
Consultant Commit Per Vintage ($ bn)	15,375	4.0	2.8	3.9
2. GP & Fund Variables				
PE Fund Size ($ bn)	15,375	3.6	1.7	4.6
First GP Fund (B)	15,375	0.228	0.000	0.419
Same State GP (B)	15,375	0.085	0.000	0.279
Fund IRR (%) [Vintage<2016]	10,242	0.112	0.109	0.123
3. LP Variables				
LP Size ($ bn)	15,375	56.6	32.4	70.7
Investor GP Exp (B)	15,375	0.486	0.000	0.500
LP Str Focus (%)	15,050	0.276	0.220	0.235
4. Access Variables				
Minimum Commitment ($ mn)	15,375	16.2	10.0	20.6
Smallest Investor Size ($ bn)	14,716	10.4	4.0	17.8
5. Board of Trustees Variables				
Board Size (#)	14,618	9.489	9.000	4.139
Public App Trustee Share (%)	14,618	0.255	0.250	0.229

Table 1.1: Descriptive Statistics

This table presents the summary statistics of the data. Panel A summarizes the commitments to private equity funds by public pension funds by providing breakdowns for private equity fund strategy. Panel B provides the strategy breakdown of average public pension fund ownership in private equity funds. Panel C presents the variables of interest that are used in the analyses.

1.4 Methodology and Empirical Results

In this paper, I evaluate the effects of asymmetric information on PPF investment decisions by aiming to answer three questions: 1) Do investment consultants create value for investors in their PE fund selection process? 2) How does PPF experience affect the use of investment consultants and fund selection performance? 3) Do PPFs use peers' investments as an information signal (i.e. herding)? Each question is empirically evaluated separately in the following sections.

1.4.1 Investment Consultants & PE Fund Selection

Investment consultants play a key role in the investment decision-making process of PPFs, and they are key middlemen building the bridge between PE investors and fund firms. They are equipped with better industry information and wider professional networks than investors.

Following these attributes, I build the first hypothesis:

Hypothesis 1: Fund selections driven by investment consultants overperform.

As introduced in the data section, data on PE fund selections driven by consultants does not exist; therefore, it is proxied with the "Consultant Commit" variable introduced in detail before. Before testing the hypothesis above, it is detrimental to assess the validity and strength of this proxy variable. To do this check, I build the following model:

$$\text{Logit}(ConsultantCommit_{i,t,s}) = \alpha + \beta_1 \ (\text{ConsultantGPExp}_{i,t,s})$$
$$+ \beta_2 \ (\text{ConsultantStrFocus}_{i,t,s}) + \beta_3 \ (\text{InvestorGPExp}_{i,t,s}) + \Gamma' X_{its} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \quad (1)$$

In the logit model above (and all models discussed later), i,t and s stand for the pension fund, vintage year and fund strategy. The model aims to assess the relationship between the binary variable which proxies for the PE fund selections driven by consultants (ConsultantCommit), the binary variable which assesses whether the consultant has any prior investments in the fund firm of interest via other clients (ConsultantGPExp), percentage of the prior commitments made by the consultant's clients in the PE strategy of interest (ConsultantStrFocus), and the binary variable which assesses whether the PPF has any prior investments in the fund firm of interest (InvestorGPExp). A good proxy should be positively related to the consultant's past relationship with the fund firm, positively related to the consultant's strategy focus and negatively related to the PPF's past relationship with the fund firm. In the model, X represents the matrix of control variables related to the PE fund and consultant. Fixed effects for the pension fund, vintage year and strategy are also included in some specifications.

Table 2 presents the results of the regressions related to the model introduced above. Binary variables are highlighted as (B), and other variables are standardized for an easier interpretation. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level (this is valid for every test result presented in this paper). Together with the three different logit models, an OLS model is presented as robustness. The last column presents the odds ratios obtained from the logistic regression, which makes it easier to interpret and discuss the results.

We observe that the obtained results are in line with the expectations from this proxy variable. The selection of PE funds belonging to fund firms with a prior relationship with the consultant is five times more likely to be highlighted as consultant-driven. On the contrary, a prior relationship with the investor makes it 27% less likely for the consultants to drive the selection. Additionally, one standard deviation increase in the percentage of prior commitments of the consultants in a PE fund's strategy increases the selection of that fund to be driven by the consultant by %44. Results are robust to controlling for PE fund size and state, the scale of the consultant activity, fund access to PE funds, and including three sets of fixed effects. Overall, the results of this analysis provide significant support for the validity of the evaluated proxy variable.

Consultant Commit (B)	Logit	Logit	Logit	OLS	Odds Ratios
Consultant GP Exp (B)	1.845***	1.802***	1.579***	0.291***	4.848***
	(0.07)	(0.08)	(0.08)	(0.01)	(0.40)
Consultant Str. Focus	0.310***	0.263***	0.363***	0.055***	1.438***
	(0.03)	(0.04)	(0.04)	(0.01)	(0.06)
Investor GP Exp (B)	-0.433***	-0.170**	-0.314***	-0.046***	0.730***
	(0.07)	(0.07)	(0.08)	(0.01)	(0.05)
PE Fund Size			0.246***	0.036***	1.279***
			(0.03)	(0.00)	(0.04)
Consultant Commit Per Vintage			0.830***	0.122***	2.293***
			(0.09)	(0.01)	(0.21)
Minimum Commitment			-0.448***	-0.063***	0.639***
			(0.05)	(0.01)	(0.04)
Smallest Investor Size			-0.082*	-0.019**	0.922*
			(0.05)	(0.01)	(0.04)
Same State GP (B)			0.034	-0.002	1.034
			(0.11)	(0.02)	(0.12)
Pension Fund FE	No	Yes	Yes	Yes	Yes
Vintage FE	No	Yes	Yes	Yes	Yes
Strategy FE	No	Yes	Yes	Yes	Yes
Pseudo / Adusted R-squared	0.142	0.250	0.303	0.343	0.303
N	13,302	13,138	12,577	12,742	12,577

Table 1.2: Consultant-Driven Deals

This table presents the results of the regressions in which the dependent variable is "Consultant Commit", a variable highlighting the fund selection observations that are more likely to be consultant-driven. The independent variables of interest are "Consultant GP Exp", which is a binary variable that takes the value of one if the consultant has a prior relationship with the fund manager through other clients, "Consultant Str. Focus" that is the percentage of total prior commitments made to the strategy of observation by all clients of the consultant, and "Investor GP Exp", a binary variable that assesses whether the investor has a prior relationship with the fund manager. Other control variables are the size of the private equity fund, total amount committed by the consultant's client for each vintage, minimum commitment amount accepted by the private equity fund, size of the smallest investor accepted into the fund and a binary variable that highlights the commitments made by an investor to a fund manager located in the same state. Binary variables are highlighted with the letter "B". All continuous variables are standardized. Limited partner, vintage year and strategy fixed effects are controlled for under different specifications. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

To test Hypothesis 1, I build the following OLS model:

$$FundIRR_{i,t,s,g} = \alpha + \beta\ (\text{ConsultantCommit}_{i,t,s,g}) + \Gamma' X_{i,t,s,g} + \theta_i + \mu_t + \nu_s + \zeta_g + e_{i,t,s,g} \tag{2}$$

The model in Equation 2 aims to test if investment consultants' fund selections perform better than internally managed PE fund selections. On top of the subscripts introduced while discussing Equation 1, g represents the GP (i.e. fund manager) of the PE fund. Table 3 presents the results. The first five columns introduce various levels of control using PE fund size, access and state, and fixed effects for vintage, strategy and PPF. Obtained coefficients are significant and robust, and they highlight an overperformance of 0.9-1.3% for consultant-driven fund selections compared to internally driven ones. However, this performance may be because consultants have access to specific fund firms instead of their informational advantages and fund selection skills. To control for this possibility, I add GP fixed effects in the last column. Nevertheless, the significance of the results prevails, albeit with a slightly lower point estimate. These results show that investment consultants contribute to the fund selection process of PE investors, and they can even pick the better-performing funds of the same fund firms.

Fund IRR	(1)	(2)	(3)	(4)	(5)	(6)
Consultant Commit (B)	0.013***	0.010***	0.010***	0.009***	0.009***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PE Fund Size			0.001	0.001	0.001	-0.006***
			(0.00)	(0.00)	(0.00)	(0.00)
Minimum Commitment				-0.005*	-0.005*	-0.005*
				(0.00)	(0.00)	(0.00)
Smallest Investor Size				-0.001	-0.000	0.000
				(0.00)	(0.00)	(0.00)
Same State GP (B)					0.030***	0.001
					(0.01)	(0.00)
Vintage FE	No	Yes	Yes	Yes	Yes	Yes
Strategy FE	No	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	No	Yes	Yes	Yes	Yes	Yes
General Partner FE	No	No	No	No	No	Yes
Adjusted R-squared	0.003	0.165	0.165	0.167	0.171	0.611
N	9,313	9,313	9,281	8,923	8,923	8,923

Table 1.3: Consultant Contribution to Fund Selection

This table presents the results of the OLS regressions in which the dependent variable is “Fund IRR”, which is the IRR of the private equity fund of observation. The independent variable of interest is “Consultant Commit”, a variable highlighting the fund selection observations that are more likely to be consultant-driven. Other control variables are the size of the private equity fund minimum commitment amount accepted by the private equity fund, size of the smallest investor accepted into the fund and a binary variable that highlights the commitments made by an investor to a fund manager located in the same state. Binary variables are highlighted with the letter ”B”. All continuous variables are standardized. Limited partner, vintage year, strategy and general partner fixed effects are controlled for under different specifications. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

The previous analysis on consultant contribution disguises significant differences in investment consultants’ experience in the PE industry, the extent of their professional networks and their capacity to obtain valuable information on fundraising PE funds. Consultants also differ in terms of the responsibilities the investor assigns them. General investment consultants play a role in all stages of the investment process, including advising on the overall strategy and asset allocation, together with choosing fund managers. Some PPFs also employ specialist consultants with particular experience in PE investments or particularly in some PE strategies.

Specialist consultants are particularly hired to assist in selecting the PE funds to invest in by using their extensive experience and professional networks in this industry. Since the specialist consultants have access to higher quality information on the fundraising PE funds, we would expect their contribution to PE fund selection to be higher:

Hypothesis 2: Specialist consultants contribute more to the PE fund selection process than generalist consultants.

To test Hypothesis 2, I use the model which is already introduced in Equation 2, but I condition it on the existence of an employed Specialist Consultant by the PPF in the observation year. The underlying assumption is general investment consultant advises on the fund selection if it is the only employed consultant. Otherwise, fund selection is advised by the specialist consultant. Table 4 presents the results. The first model includes three sets of fixed effects. The second model adds control variables. The final model introduces the fixed effects for general partners. Each model is presented by splitting the samples based on the existence of a specialist consultant. The results show that the contribution of consultants observed in the previous analysis is solely attributable to specialist consultants. These results support the interpretation that specialist PE consultants have deeper industry knowledge, expertise and wider networks which would help them make more informed decisions about which PE fund to choose.

How do specialist PE consultants use their PE expertise and informational advantages? What do they do differently in fund selection to take advantage of their strengths? It would be logical to expect that their extensive networks would help them ease the "fund access" issue faced by the investors by being able to let them into PE funds that are more difficult to get into. Also, given their capacity to access and process industry-related information, we can expect them to lead their customers into commitments to PE funds with greater information asymmetry. The next hypothesis summarizes these expectations:

Hypothesis 3: Specialist PE consultants provide better access to PE funds and lead PPFs into investments with greater information asymmetry.

To test Hypothesis 3, I use the following OLS models:

	(1)	(2)	(3)	(4)	(5)	(6)
Fund IRR	No Specialist	Specialist	No Specialist	Specialist	No Specialist	Specialist
Consultant Commit (B)	0.003	0.017***	0.001	0.016***	-0.001	0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PE Fund Size			0.001	0.000	-0.006***	-0.006***
			(0.00)	(0.00)	(0.00)	(0.00)
Minimum Commitment			-0.004	-0.005	-0.005	-0.005
			(0.00)	(0.00)	(0.00)	(0.00)
Smallest Investor Size			0.001	-0.001	0.001	-0.000
			(0.00)	(0.00)	(0.00)	(0.00)
Same State GP (B)			0.024***	0.032***	0.001	-0.000
			(0.01)	(0.01)	(0.01)	(0.00)
Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
General Partner FE	No	No	No	No	Yes	Yes
Adjusted R-squared	0.155	0.186	0.155	0.194	0.557	0.628
N	3,960	5,353	3,733	5,190	3,733	5,190

Table 1.4: Contribution by Consultant Type

This table presents the results of the OLS regressions in which the dependent variable is "Fund IRR", which is the IRR of the private equity fund of observation. The independent variable of interest is "Consultant Commit", a variable highlighting the fund selection observations that are more likely to be consultant-driven. Other control variables are the size of the private equity fund minimum commitment amount accepted by the private equity fund, size of the smallest investor accepted into the fund and a binary variable that highlights the commitments made by an investor to a fund manager located in the same state. Binary variables are highlighted with the letter "B". All continuous variables are standardized. Limited partner, vintage year and strategy fixed effects are controlled for under different specifications. Three different models are separately evaluated for two subsamples, based on whether the fund consultant is a private equity specialist or not. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

$$SmallestInvestorSize_{i,t,s} = \alpha + \beta\,(\text{SpecialistConsultant}_{i,t,s}) + \Gamma' X_{i,t,s} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \tag{3a}$$

$$LowRiskStrategy_{i,t,s} = \alpha + \beta\,(\text{SpecialistConsultant}_{i,t,s}) + \Gamma' X_{i,t,s} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \tag{3b}$$

$$UnrelatedGP_{i,t,s} = \alpha + \beta\,(\text{SpecialistConsultant}_{i,t,s}) + \Gamma' X_{i,t,s} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \tag{3c}$$

The models above evaluate the relationship between employing a specialist consultant and choosing funds with difficult access/high information asymmetry. "SmallestInvestorSize" is the size of the PPF with the smallest AUM within the investors of the PE fund other than the PPF of the observation, representing the difficulty of accessing this fund as an investor. "LowRiskStrategy" is a binary variable that highlights the PE funds with comparably lower investment risk. "UnrelatedGP" highlights the PE funds that are managed by fund firms which do not have any prior investment relationship with the PPF of interest. All of the models will be separately evaluated for consultant-driven and internally-driven deals. For the PE fund selections that are driven by the consultants, given the informational advantages of specialist consultants and their experience in the PE industry, we would expect them to lead their clients towards PE funds that are more difficult to access, have riskier strategies and are managed by fund firms that are unrelated to the PPF. However, for the selections that are driven internally, we would expect to observe less influence of the consultant type.

Table 5 presents the results. Column blocks represent the three models introduced above. Each model is separately evaluated for consultant-driven (ConsultantCommit=1) and internally-driven (ConsultantCommit=0) fund selections. In the left block, we observe that consultant-driven deals of specialist consultants are done to PE funds that are 13.7% larger minimum accepted investor size. For the internally driven deals, however, we observe no significant difference. These results suggest that specialist consultants use their networks to create better access to PPFs, which the investors cannot achieve themselves. In the second block, we observe that tendency of the specialist consultants to invest in a low-risk PE strategy is 8% lower compared to generalist consultants. This figure is also statistically indistinguishable from 0 for the internally-driven selections. Finally, in the last block, we observe that specialist consultants have a 5.3% higher probability of leading their customers to form investment relationships with previously unrelated fund firms. This result is also close to 0 for internally driven deals.

Overall, the results presented in Table 5 fully support Hypothesis 3. Specialist consultants use their professional networks and expertise to lead their customers into hard-to-access funds, and they use their informational advantages to push their clients out of their comfort zone by making them invest in riskier strategies and new fund firms.

1.4.2 Board Experience & PE Fund Selection

The previous section investigated the role of investment consultants as a tool for better access to high-quality information. Consultants, however, are not the only source of information for PPF trustees. Fund selection is a complex process with multiple parties involved. Depending on their size and available resources, PPFs have an investment team led by a Chief Investment Officer. The investment team and consultants support the trustees in the investment committee, in which possible investment alternatives are discussed. Final decisions among the possible alternatives are then made during the board of trustee meetings. So, together with the contribution of consultants, the backgrounds of trustees are a significant determinant of the fund selection performance.

Andonov, Hochberg and Rauh (2018) evaluate the effect of the finance and asset manage-

	Smallest Inv. Size		Low-Risk Strategy		Unrelated GP	
	Consultant	Internal	Consultant	Internal	Consultant	Internal
Specialist Consultant (B)	0.137***	-0.021	-0.081***	-0.020	0.053***	0.007
	(0.04)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)
Pension Fund Size	0.121***	0.288***	-0.012	0.001	-0.066***	-0.076***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)
Pension Fund Experience	0.005	0.025	0.013	0.003	-0.043***	-0.067***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Fund Sequence	0.001	-0.009	0.069***	0.091***	-0.125***	-0.132***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Commitment Count Per Vintage	0.129***	0.127***	-0.026**	-0.014	-0.032**	0.001
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
PE Fund Size	-0.006	0.019**	-0.002	-0.007	0.003	0.002
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
# of Commitments per PE Fund	-0.235***	-0.243***	-0.105***	-0.099***	-0.081***	-0.046***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Minimum Commitment	0.617***	0.389***	0.048***	0.069***	-0.012	-0.009
	(0.03)	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)
Smallest Investor Size			-0.145***	-0.156***	-0.001	0.003
			(0.01)	(0.01)	(0.01)	(0.01)
Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	No	No	Yes	Yes
Adjusted R-squared	0.542	0.581	0.197	0.188	0.274	0.264
N	5,851	8,759	5,851	8,759	5,851	8,759

Table 1.5: Fund Selection Practices of Specialist Consultants

This table presents the results of the three OLS regressions in which the dependent variables are "Smallest Investor Size", which is the size of the smallest investor accepted in a private equity fund, "Low-Risk Strategy", a binary variable that highlights the private equity strategies with lower riskiness, and "Unrelated GP", a binary variable that highlights the fund manager that the investor does not have a prior relationship. The independent variable of interest is "Specialist Consultant", a binary variable highlighting whether the consultant of the investor is a private equity specialist or not. Binary variables are highlighted with the letter "B". All continuous variables are standardized. Vintage year and strategy fixed effects are controlled for under different specifications. The models are separately evaluated for two subsamples, based on whether the fund selection is driven internally or by the consultants. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

ment experience of trustees and find a positive and significant relationship. Relevant trustee experience leads to consistently superior fund selection performance. The paper also provides significant insight into the experiences of trustees with different backgrounds. "Participant" trustees represent the plan participants; therefore, they have limited relevant experience. "State" trustees have more relevant experience, but the political requirements of their office dilute their decision-making process. Additionally, they favour same-state investments due to political pressures (Hochberg and Rauh, 2013). "Public" members, however, are members of the public appointed explicitly to contribute to the PPF governance, and these members possess much higher relevant experience compared to the trustees from other backgrounds. Therefore, in the absence of data on trustee experience, I use the percentage of appointed public members in a board of trustees as a proxy for relevant trustee experience.

Building on the discussions above and the previous findings presented by the academic literature, we would expect the level of experience of the board members to affect the amount of information they can access by themselves, the level of support they seek from the consultants, and the performance of the fund selections that are driven internally. These expectations lead us to form the following two hypotheses:

Hypothesis 4: PPFs with more experienced boards seek less support from investment consultants.

Hypothesis 5: PPFs with more experienced boards perform better in internally-driven fund selections.

To test Hypothesis 4, I build the following Logit model:

$$\text{Logit}(ConsultantCommit_{i,t,s}) = \alpha + \beta\ (\text{PublicAppTrusteeShare}_{i,t,s}) + \Gamma' X_{its} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \quad (4)$$

This model aims to evaluate the relationship between the percentage of appointed public trustees on the board and the binary variable highlighting the fund selections driven by consultants. In light of the discussion made in the previous paragraphs, we would expect the boards with more experienced trustees to rely less on consultants, hence a negative beta coefficient.

Table 6 presents the results. Similar to the previous tests that involved logit models, the first block (first four columns for this analysis) involves logit models with an increasing number of fixed effects and control variables. 5th column is the OLS model, which is presented as a robustness check. The last column presents the odds ratios. All variables, except the binary ones, are standardized for ease of interpretation. In line with the hypothesis, we obtain a negative and significant coefficient for the variable of interest. One standard deviation increase in the percentage of appointed public trustees decreases the reliance on consultants by around 20%.

The final step in this section is to test how the trustee experience affects fund selection performance in internally driven fund selections. To test Hypothesis 6, the following OLS model is used:

$$FundIRR_{i,t,s} = \alpha + \beta\ (\text{PublicAppTrusteeShare}_{i,t,s}) + \Gamma' X_{i,t,s} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \quad (5)$$

The model in Equation 5 aims to assess how the level of trustee experience affects fund selection performance. The difference compared to Andonov, Hochberg and Rauh (2018), which already presented a positive relationship between trustee experience and performance, is the

	(1)	(2)	(3)	(4)	(5)	(6)
Consultant Commit (B)	Logit	Logit	Logit	Logit	OLS	Odds Ratios
Appointed Public Trustee %	-0.202***	-0.200***	-0.207***	-0.230***	-0.046***	0.795***
	(0.07)	(0.07)	(0.07)	(0.08)	(0.01)	(0.06)
Pension Fund Size	-0.192*	-0.182*	-0.219**	-0.285**	-0.059**	0.752**
	(0.11)	(0.11)	(0.11)	(0.14)	(0.03)	(0.10)
Pension Fund Experience	-0.127	-0.127*	-0.127*	-0.150*	-0.030*	0.861*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.02)	(0.07)
Specialist Consultant (B)	1.009***	0.989***	0.944***	1.027***	0.211***	2.793***
	(0.19)	(0.19)	(0.19)	(0.21)	(0.04)	(0.60)
PE Fund Size				-0.046*	-0.009*	0.955*
				(0.03)	(0.01)	(0.02)
Minimum Commitment				-0.217***	-0.033***	0.805***
				(0.06)	(0.01)	(0.05)
Smallest Investor Size				0.168***	0.031***	1.183***
				(0.06)	(0.01)	(0.07)
Board Size				-0.007	-0.001	0.993
				(0.02)	(0.01)	(0.02)
# of Commitments per PE Fund				0.708***	0.149***	2.031***
				(0.05)	(0.01)	(0.10)
Vintage FE	No	Yes	Yes	Yes	Yes	Yes
Strategy FE	No	No	Yes	Yes	Yes	Yes
Pseudo Adjusted R-squared	0.039	0.046	0.056	0.139	0.173	0.139
N	13,690	13,675	13,675	13,106	13,113	13,106

Table 1.6: Trustee Experience & Reliance on Consultants

This table presents the results of the regressions in which the dependent variable is "Consultant Commit", a variable highlighting the fund selection observations that are more likely to be consultant-driven. The independent variable of interest is "Appointed Public Trustee %", which is the percentage of appointed public trustees in a pension fund board. Binary variables are highlighted with the letter "B". All continuous variables are standardized. Limited partner, vintage year and strategy fixed effects are controlled for under different specifications. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

fact that the model will be evaluated conditional on the selection being driven by consultants (ConsultantCommit=1) or driven internally (ConsultantCommit=0). We would expect the contribution of the trustees to be observed for internally driven selections.

Table 7 presents the results of the analysis. Two blocks present the results for three different models, separately for consultant-driven and internally driven deals. As before, all independent variables except the binary ones are standardized. The results are in support of hypothesis 5. Experienced trustees contribute to fund selection when the process is internally driven. One standard deviation increase in the percentage of appointed public trustees leads to an increase in selected fund IRR by 0.6%. The contribution, however, is null for the deals driven by consultants.

Overall, the results from the analyses presented in this section support the argument that access to information is critical. PPFs rely more on their capabilities if they have the necessary expertise and means to access high-quality information by themselves, but they rely on their consultants otherwise.

Fund IRR	Consultant-Driven Selections (1)	(2)	(3)	Internally-Driven Selections (4)	(5)	(6)
Appointed Public Trustee %	-0.000	-0.000	-0.000	0.006**	0.006**	0.006**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pension Fund Size	0.010***	0.008***	0.009***	0.004	0.002	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Same State GP (B)	0.030***	0.028***	0.028***	0.032***	0.030***	0.030***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Minimum Commitment	-0.007*	-0.001	-0.001	-0.005	-0.003	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Smallest Investor Size	-0.001	0.004	0.004	0.001	0.004	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pension Fund Experience		-0.002	-0.002		0.001	0.001
		(0.00)	(0.00)		(0.00)	(0.00)
# of Commitments Per PE Fund		0.015***	0.015***		0.009***	0.008***
		(0.00)	(0.00)		(0.00)	(0.00)
PE Fund Size		-0.004***	-0.004***		-0.003*	-0.003*
		(0.00)	(0.00)		(0.00)	(0.00)
Specialist Consultant (B)			0.002			-0.002
			(0.01)			(0.00)
Consultant Commitment Per Vintage			-0.002			-0.001
			(0.00)			(0.00)
Board Size			0.000			-0.000
			(0.00)			(0.00)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.187	0.194	0.193	0.161	0.163	0.163
N	3,771	3,771	3,771	4,990	4,990	4,990

Table 1.7: Trustee Experience & Fund Selection Performance

This table presents the results of the regressions in which the dependent variable is "Fund IRR", which is the IRR of the private equity fund of observation. The independent variable of interest is "Appointed Public Trustee %", which is the percentage of appointed public trustees in a pension fund board. Binary variables are highlighted with the letter "B". All continuous variables are standardized. Limited partner, vintage year and strategy fixed effects are controlled for under different specifications. Three models are evaluated separately for two subsections, based on whether the fund selection is driven interally or by the consultants. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

1.4.3 Information Signals from Peer Commitments & PE Fund Selection

As discussed in the earlier sections of the paper, academic literature documents the herd-like behaviour of institutional investors, specifically pension funds, in their investment decisions. One of the main motivations of the observed herd behaviour is to alleviate informational disadvantages by using the investments of peer institutions as valuable information signals. Given the adversity of the information asymmetry in the PE industry and the difficulty of assessing the quality of fund managers and expected returns of PE funds, we would expect the institutional investors to assign a high value to the observed commitment behaviours of other investors while trying to decide which fund to invest in.

Hypothesis 6: PPFs herd in their PE commitment decisions.

Assessing herd behaviour in the PE industry is quite challenging due to the completely different nature of PE investments compared to the traditional asset classes (e.g. stocks, bonds). Lakonishok, Shleifer and Vishny (1992) measure herding in the stock market as the investors' tendency to buy or sell particular stocks simultaneously. On the other hand, Christie and Huang (1995) use the dispersion of investor returns around the market return to measure herd behaviour. These measurements rely on the liquid and continuous nature of the traditional markets, in which numerous investors constantly invest, re-invest and liquidate assets. However, investing in a PE fund is a one-time decision that is, under normal circumstances, difficult to change during the fund's life. Moreover, a particular PE fund has only a few dozen investors on average, a figure dramatically low compared to public equities and bonds.

This paper introduces a 2-step methodology to assess herd behaviour in PE commitments, which considers the PE industry's peculiar characteristics. According to this methodology, a commitment made to a PE fund by a PPF releases an information signal to peers, and the commitment amount determines the magnitude of this signal. In the first step, the magnitude of this information signal is calculated as the unexplained portion of the commitment amount made to a specific fund using the following regression model:

$$CommitmentAmount_{i,t,s} = \alpha + \beta_1(YearlyTotalCommitments_{i,t,s}) + \beta_2(PEFundSize_{i,t,s}) + \beta_3(MinimumCommitment_{i,t,s}) + \theta_i + \mu_t + \nu_s + AbnCommit_{i,t,s} \tag{6}$$

In the model in Equation 6, the commitment amount by a PPF to a PE fund is regressed on the total yearly commitment of that PPF to the PE industry, the size of the PE fund and minimum commitment to the same fund, together with three sets of fixed effects. The error term constitutes the unexplained, abnormal commitment and is labelled as "AbnCommit". This variable represents the scale of the information signal.

In the second step of the methodology, I evaluate how the total commitments of other PPFs (measured as a percentage of PE fund size) that are made before and after the observation of interest is related to this informational signal:

$$PFEarlyCommitShare_{i,t,s} = \alpha + + AbnCommit_{i,t,s} + \Gamma' X_{i,t,s} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \tag{7a}$$

$$PFLateCommitShare_{i,t,s} = \alpha + + AbnCommit_{i,t,s} + \Gamma' X_{i,t,s} + \theta_i + \mu_t + \nu_s + e_{i,t,s} \tag{7b}$$

For our results to imply herd behaviour among PPFs in their PE fund selections, we should observe a positive and significant relationship between the informational signal and the "Late" commitments, while the relationship with early commitments should be fairly small.

The implementation of this methodology, however, poses additional challenges due to the lack of data on precise commitment dates. This methodology requires knowledge of the exact date when the PPF decided/made this commitment, which is only available for half of the sample. Observations with missing date data are therefore not used in this analysis. This action relies on an inherent assumption that the unavailability of the date data does not have any structural reasons that might bias the results. Robustness tests are also conducted to support the claims that will be made using the methodology mentioned above.

Table 8 presents the results of the tests based on the methodology discussed above. The left block of the table is based on Equation 7a, which evaluates the relationship between the informational signal released by a PPF and the total PPF ownership (in standardized percentages of fund size) that happened before this signal by other PPFs. The right block of the table makes the same evaluation for the PPF ownership after the signal. Together with the usual control variables, "Commitment Date" is added as an additional variable to control for the possibility that the scale of the commitments and their timings during the fundraising period may be correlated. This variable defines each commitment date as the days passed from the first commitment made to the fund and standardizes these dates by dividing them by the total fundraising days for this fund. The results presented in Table 8 support Hypothesis 6. The informational signal (i.e. magnitude of the commitment) released by a PE fund has no relationship with past commitments but is significantly and positively related to future commitments, which signals herd behaviour.

Table 9 provides the results of several tests conducted to check the results presented in Table 8. In the first column, I skip the first step of the methodology introduced in Equation 6 and introduce "Commit Ratio" as an alternative variable assessing the scale of the information signal. This variable compares the commitment made by a PPF to a specific PE fund with the average commitment made by the same PPF during the 3-year window around the observation of interest. The distribution of the variable is normalized by a logarithmic transformation afterwards. The other two columns introduce strict data filtering to ensure the lack of commitment date data does not bias the results. In the second column, I filter out all PE funds with less than 80% of available commitment date data. And in the final column, I focus on PE funds with at least ten commitments with available commitment data. The results hold in each of

	Pre-Commitment			Post-Commitment		
Other PF Ownership %	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal Commitment	0.013	0.008	-0.005	0.122***	0.080***	0.078***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Commitment Date		1.430***	1.430***		-1.285***	-1.282***
		(0.04)	(0.04)		(0.03)	(0.04)
PE Fund Size		-0.032**	-0.043***		-0.037***	-0.040***
		(0.02)	(0.02)		(0.01)	(0.01)
Minimum Commitment		-0.019	-0.018		-0.022*	-0.021
		(0.02)	(0.02)		(0.01)	(0.01)
Same State GP			-0.029			0.019
			(0.05)			(0.06)
Strategy Sequence			0.027			0.015
			(0.02)			(0.01)
Limited Partner FE	No	Yes	Yes	No	Yes	Yes
Commitment Year FE	No	Yes	Yes	No	Yes	Yes
Strategy FE	No	Yes	Yes	No	Yes	Yes
Adjusted R-squared	-0.000	0.307	0.307	0.003	0.340	0.342
N	6,745	5,954	5,850	6,746	5,954	5,850

Table 1.8: Pension Fund Herding - Pre/Post Commitment

This table presents the results of the regressions in which the dependent variable is “Other PF Ownership %”, which is the percentage of the private equity fund size that are owned by public pension funds, other than the one of the observation. The independent variable of interest is “Abnormal Commitment”, unexplained amount of commitment made to a private equity fund, which is used as a proxy for the magnitude of information signal. All continuous variables are standardized. Limited partner, commitment year and strategy fixed effects are controlled for under different specifications. The dependent variable is separately calculated and evaluated based on whether the other PF ownership occurs before or after the commitment of the observation. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

these robustness tests.

The final step of this section is to evaluate the conditions under which herd behaviour surges. Given that high-quality information is crucial in choosing PE funds, the source of this information signal should also matter. It would be logical to expect that signals released by large and more experienced PPFs trigger a greater herd behaviour. Additionally, the need to herd would be higher for funds belonging to PE strategies with higher investment risk. The following hypothesis summarizes these expectations:

Hypothesis 7: Informational signals from large and more experienced PPFs are more effective herding triggers. Additionally, herd behaviour is higher for riskier strategies, for which information quality matters more.

Table 10 uses the methodology introduced by Equations 6 and 7 and evaluates three groups of information sources based on PPF size clusters. Information signals are not significantly related to commitments before the signal for each group. For the commitments after the signal, however, we observe that although small PPFs do not trigger herd behaviour, large PPFs are followed by a significant increase in commitments from other PPFs.

	Pre-Commitment			Post-Commitment		
Other PF Ownership %	(1)	(2)	(3)	(4)	(5)	(6)
Commit Ratio	-0.027			0.159***		
	(0.06)			(0.06)		
Abnormal Commitment		0.044	-0.012		0.138**	0.203***
		(0.07)	(0.08)		(0.05)	(0.06)
Commitment Date	1.430***	1.875***	2.287***	-1.280***	-1.617***	-1.883***
	(0.05)	(0.09)	(0.13)	(0.04)	(0.07)	(0.09)
PE Fund Size	-0.040**	-0.070	-0.222***	-0.059***	-0.046	-0.143***
	(0.02)	(0.08)	(0.03)	(0.01)	(0.06)	(0.02)
Minimum Commitment	-0.016	-0.033	-0.083	-0.030**	0.006	0.035
	(0.02)	(0.04)	(0.06)	(0.01)	(0.04)	(0.04)
Same State GP	-0.028	-0.081	-0.025	0.018	0.233	0.033
	(0.05)	(0.13)	(0.08)	(0.06)	(0.15)	(0.09)
Strategy Sequence	0.027	0.061	0.012	0.015	0.088***	-0.032
	(0.02)	(0.05)	(0.04)	(0.01)	(0.03)	(0.03)
Limited Partner FE	Yes	Yes	Yes	Yes	Yes	Yes
Commitment Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.307	0.338	0.460	0.342	0.375	0.489
N	5,850	1,508	1,193	5,850	1,508	1,193

Table 1.9: Pension Fund Herding - Robustness

This table presents the results of the robustness tests in which the dependent variable is "Other PF Ownership %", which is the percentage of the private equity fund size that are owned by public pension funds, other than the one of the observation. The independent variables of interest are "Abnormal Commitment", unexplained amount of commitment made to a private equity fund, which is used as a proxy for the magnitude of information signal, and "Commit Ratio", the ratio of a commitment made to a fund by an investor, to the average commitments of the same investor during the 3-year window around the commitment of interest. All continuous variables are standardized. Limited partner, commitment year and strategy fixed effects are controlled for under different specifications. The dependent variable is separately calculated and evaluated based on whether the other PF ownership occurs before or after the commitment of the observation. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

	Pre-Commitment			Post-Commitment		
Other PF Ownership %	Small PF	Medium PF	Large PF	Small PF	Medium PF	Large PF
Abnormal Commitment	0.034	-0.011	-0.026	0.005	0.091**	0.110**
	(0.08)	(0.05)	(0.04)	(0.06)	(0.03)	(0.05)
Commitment Date	1.446***	1.400***	1.446***	-1.265***	-1.260***	-1.334***
	(0.08)	(0.08)	(0.08)	(0.06)	(0.04)	(0.07)
PE Fund Size	-0.085**	0.001	-0.054**	-0.060***	-0.012	-0.053***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Minimum Commitment	0.033	-0.010	-0.067*	-0.012	-0.053***	0.002
	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)
Same State GP	0.020	0.024	-0.053	-0.102	0.207**	-0.040
	(0.12)	(0.07)	(0.07)	(0.06)	(0.10)	(0.08)
Strategy Sequence	0.025	0.056**	0.001	0.029	0.010	0.005
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Limited Partner FE	Yes	Yes	Yes	Yes	Yes	Yes
Commitment Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.259	0.323	0.323	0.330	0.339	0.361
N	1,546	2,231	2,073	1,546	2,231	2,073

Table 1.10: Herding Triggers - PF Size

This table presents the results of the regressions in which the dependent variable is "Other PF Ownership %", which is the percentage of the private equity fund size that are owned by public pension funds, other than the one of the observation. The independent variable of interest is "Abnormal Commitment", unexplained amount of commitment made to a private equity fund, which is used as a proxy for the magnitude of information signal. All continuous variables are standardized. Limited partner, commitment year and strategy fixed effects are controlled for under different specifications. The dependent variable is separately calculated based on whether the other PF ownership occurs before or after the commitment of the observation, and evaluated for three subgroups based on the size of the pension fund which makes the commitment. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

Table 11 moves one step forward by evaluating the difference in reaction to signals sourced by PPFs experienced/inexperienced in PE investing, controlling for the size of the PPF. The results are interesting. PPFs with high PE experience trigger herd behaviour from others, whereas investment decisions of inexperienced PPFs are affected by the commitments made to the PE fund before them. Both results are in line with herd behaviour. Reputable investors lead, while inexperienced ones follow others.

	Pre-Commitment		Post-Commitment	
Other PF Ownership %	Low Experience	High Experience	Low Experience	High Experience
Abnormal Commitment	0.090*	-0.030	0.003	0.129***
	(0.05)	(0.04)	(0.04)	(0.03)
Commitment Date	1.360***	1.386***	-1.155***	-1.248***
	(0.06)	(0.06)	(0.05)	(0.07)
PE Fund Size	-0.000	-0.059***	-0.049***	-0.034**
	(0.02)	(0.02)	(0.01)	(0.01)
LP Size	0.039*	-0.052	-0.014	-0.007
	(0.02)	(0.06)	(0.02)	(0.04)
Minimum Commitment	-0.023	-0.000	-0.019	-0.031
	(0.02)	(0.03)	(0.02)	(0.02)
Same State GP	0.044	0.002	0.029	-0.038
	(0.07)	(0.07)	(0.07)	(0.06)
Strategy Sequence	-0.012	0.047*	0.031**	0.007
	(0.02)	(0.02)	(0.01)	(0.02)
Commitment Year FE	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.283	0.292	0.288	0.349
N	3,279	2,571	3,279	2,571

Table 1.11: Herding Triggers - PF Experience

This table presents the results of the regressions in which the dependent variable is “Other PF Ownership %”, which is the percentage of the private equity fund size that are owned by public pension funds, other than the one of the observation. The independent variable of interest is “Abnormal Commitment”, unexplained amount of commitment made to a private equity fund, which is used as a proxy for the magnitude of information signal. All continuous variables are standardized. Limited partner, commitment year and strategy fixed effects are controlled for under different specifications. The dependent variable is separately calculated based on whether the other PF ownership occurs before or after the commitment of the observation, and evaluated for two subgroups based on the experience of the pension fund which makes the commitment. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

Finally, Table 12 presents the results of the tests in which herd behaviour is evaluated for two different PE strategy risk groups. As expected, herd behaviour is triggered following an informational signal only for the risky strategies, for which high-quality information is more important.

	Pre-Commitment		Post-Commitment	
Other PF Ownership %	Low Risk	High Risk	Low Risk	High Risk
Abnormal Commitment	-0.026	0.005	-0.062	0.108***
	(0.09)	(0.03)	(0.06)	(0.03)
Commitment Date	1.454***	1.438***	-1.180***	-1.315***
	(0.07)	(0.05)	(0.06)	(0.04)
PE Fund Size	-0.269***	-0.010	-0.193***	-0.017
	(0.05)	(0.02)	(0.02)	(0.01)
Minimum Commitment	0.034	-0.030	-0.011	-0.020
	(0.05)	(0.02)	(0.02)	(0.02)
Same State GP	0.163	-0.049	-0.111	0.048
	(0.11)	(0.05)	(0.12)	(0.06)
Strategy Sequence	-0.022	0.048***	0.028	0.012
	(0.03)	(0.02)	(0.02)	(0.01)
Limited Partner FE	Yes	Yes	Yes	Yes
Commitment Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.292	0.327	0.320	0.358
N	1,322	4,528	1,322	4,528

Table 1.12: Herding Triggers - Strategy Riskiness

This table presents the results of the regressions in which the dependent variable is "Other PF Ownership %", which is the percentage of the private equity fund size that are owned by public pension funds, other than the one of the observation. The independent variable of interest is "Abnormal Commitment", unexplained amount of commitment made to a private equity fund, which is used as a proxy for the magnitude of information signal. All continuous variables are standardized. Limited partner, commitment year and strategy fixed effects are controlled for under different specifications. The dependent variable is separately calculated based on whether the other PF ownership occurs before or after the commitment of the observation, and evaluated for two subgroups based on the riskiness of the fund strategy. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the LP level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

Results presented in Tables 10 to 12 align with Hypothesis 7. The source of the information signal is important for PPFs; they value the information released by larger and more experienced PPFs more than others. Additionally, access to information matters more when there is more risk involved. All of these findings support the findings of Sias (2004), Raddatz and Schmukler (2013) and Cai et a. (2019), which provide evidence that PPFs herd more when information asymmetry is greater.

1.5 Conclusions

Despite the growing popularity of private equity investments among institutional investors, academic literature provides little insight into what factors affect their fund selection. Information asymmetry between investors and fund managers is one of the most important characteristics of the private equity industry. Yet we know next to nothing about what investors do to access high-quality information about the funds they consider investing in. This paper evaluates three different sources of information that investors might be taking advantage of to alleviate information-related problems.

First, the paper evaluates the use of investment consultants in private equity fund selection. I show that consultants add value to the fund selection process, and the main contribution is owed to specialist private equity consultants with better access to information and wider professional networks. These consultants use their advantages to lead their clients to funds that are harder to access, riskier strategies, and fund managers that are less experienced.

Second, the experience of pension fund trustees matters in the performance of fund selections and the level of required consultant support during the fund selection process. Pension funds that employ more experienced trustees require less consultant support during fund selection. Additionally, these pension funds perform better in internally-driven fund selections.

Finally, the paper evaluates herding as a potential tool for accessing information. The amount committed in a PE fund acts as an information signal for the other pension funds, and the magnitude of this signal affects the total amount of new commitments received to the PE fund. The credibility of the signal source and the level of information asymmetry also affect this herd behaviour. Larger and more experienced PE funds trigger a higher level of herd behaviour. Moreover, herding is only visible for riskier strategies, where wrong investment decisions result in more severe consequences.

Several avenues remain for future research. First, this study focuses on public pension funds in the United States. Extending the sample to include other institutional investor types and other geographical locations would yield significant depth to our understanding of how institutional investors make private equity investment decisions. Additionally, access to detailed data on consultant proposals and trustee experience would let researchers significantly extend the scope of the analysis presented in this paper.

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Chapter 2

Biases in Private Equity Returns

Abstract

Private Equity (PE) has grown into a substantial asset class, but there remain major problems with measuring PE fund returns. Investors continue to use the internal rate of return (IRR) as a key measure of fund performance. It is well known that early returns of cash can have a substantial impact on fund IRRs. Still, the magnitude and causes of this effect have not previously been systematically analysed. We demonstrate that the IRR is affected by two biases: a convexity bias and a "quit-whilst-ahead" bias arising because the returns on PE projects tend to covary with their durations. Both bias the IRRs of PE funds upwards. Using a range of parametric and non-parametric estimation techniques, we show that these biases boost fund IRRs by an average of around 3% per annum - a significant proportion of the average net PE fund IRR (around 12% per annum). Fund cash multiples and PMEs become similarly biased if they are annualized to make them comparable with other assets. We further demonstrate that alternative performance measures which have been suggested by practitioners are also biased, which confirms how poorly understood these effects are. Failure to take proper account of these biases is likely to lead investors to badly misinformed investment decisions.

2.1 Introduction

The PE sector has grown massively over recent years: US Private Equity funds now manage $6 trillion (2021q4, Preqin). However, measuring the returns generated by PE funds remains very problematic. Funds' valuations of the assets they hold are generally regarded as unreliable, so investors rely instead on performance measures derived from the cashflows between PE funds and investors, especially the internal rate of return (IRR).

Other annualized return measures, such as the Public Market Equivalent (PME) and Modified IRR (MIRR) are used in academic studies but are not generally published by funds. Funds do publish their cash multiples, but these take no account of the time taken to return this cash to investors and so cannot be directly compared to the annualized returns generally used for other asset classes. For these reasons, investors have little choice but to use the historic IRRs recorded by PE funds as the basis for choosing their strategic asset allocation to PE.

It is well known that IRRs can be strongly affected by early cash distributions from funds to investors. This effect is generally explained as being due to investors being unable to reinvest this cash at a rate equivalent to the IRR. However, this is not a helpful explanation since it gives no account of the underlying causes of the effect or its likely size. Instead, we demonstrate two biases in these IRRs. We estimate the size of these biases, demonstrating that they are economically significant in overstating the return investors can expect from holding a strategic allocation to PE. These biases are not the result of deliberate manipulation by fund managers but are inherent in the statistical distribution of the cashflows generated by PE projects.

These biases must be taken into account if investors are to make like-for-like comparisons between PE returns and those achieved on other assets. Failure to do so will lead investors to misinformed asset allocation decisions.

Investment professionals have proposed variants of the IRR to measure the extent to which funds outperform listed equity indices (e.g. direct alpha, ICM/PME, PME+ and mPME). We demonstrate in Section 8 that these measures suffer from the same biases as the original IRRs. This confirms that the effects of early cash returns on fund IRRs remain poorly understood.

2.2 Literature Review

Liquid asset classes such as exchange-traded public equity can be marked-to-market every day, making it easy to calculate returns over any chosen period. But market values are not available for the illiquid assets held by PE funds. FASB has since 2008 required US funds to release periodic fair value estimates of their assets. Before this, fund managers were generally thought to keep their valuations artificially low, often at their purchase price. However, PE fund managers are now widely believed to manipulate the valuations of their existing funds in order to encourage investors into new funds that they are starting (e.g. Jenkinson et al. (2013) and Brown et al. (2019), although Huther (2018) disagrees). The SEC has expressed concern about such manipulation. In the absence of reliable valuations, investors are forced to rely on performance measures derived from the cashflows between PE funds and their investors. The key measures are the internal rate of return (IRR) on these cashflows and the cash multiple.

The cash multiple records the total cash returned to investors over the lifetime of the fund as a multiple of the total cash invested. The Public Market Equivalent (PME) is an alternative to the cash multiple, which discounts the cashflows to a common base year before taking the ratio[1]. Academic studies have shown that the cash multiple and PME are both good indicators of relative fund performance (Harris, Jenkinson, and Kaplan, 2014), and PMEs have been used to assess the aggregate performance of the PE sector (Kaplan and Schoar, 2005). However, funds generally do not publish their performance as PMEs. They do publish the cash multiples that they achieve, and these are widely used to compare the performance of different funds. Still, in choosing their strategic asset allocations, investors require a measure of annualized PE returns that they can compare with the annual returns reported for other asset classes, such as bonds and listed equities. For this purpose, they have little alternative but to use the IRR.

A number of papers have estimated the factor exposures of PE funds in aggregate. For buyout funds, some studies find market betas above unity, some below[2], with significant additional exposure to small (SMB) and value (HML) equity factors (Ewens et al., 2013; Jegadeesh et al., 2015 and Ang et al., 2018). Estimated alphas range from -0.3% to +1% per annum. Driessen et al. (2012) is an outlier reporting much larger market exposure (1.7) and a -1% alpha. These studies report higher market betas for venture capital funds but a similar range of alphas. It is, of course, very important to distinguish risk premia from outperformance, but this is not the focus of our paper. Continued massive capital inflows suggest that the low alphas reported by these studies do not appear to have diminished investor appetite for PE, and Gompers et

[1] The PME is defined as the present value of total cash flows released by the fund divided by the present value of the total cash invested, with present values calculated by discounting using an appropriate benchmark such as the total return on the S&P500 index (Kaplan and Schoar, 2005). A PME greater than unity shows that the fund concerned outperforms this index. As shown below, the cash multiple can be regarded as a special case of the PME, with the discount factor set to zero. Practitioners have proposed various alternative performance measures derived from fund IRRs. Confusingly, some of these are also referred to as the PME. We consider these in Section 8.

[2] Ewens et al. (2013), find β=0.93 for a sample of BO and VC funds. Jegadeesh, Kraussl, Pollet (2015) find β=0.95 for BO, β=1.19 for VC. Ewens, Jones, Rhodes-Kropf (2013) β=0.72 for BO, β=1.23 for VC. Driessen, Lin, Phalippou (2012) β=1.3 for BO, β=2.73 for VC. Ang et al. (2018) derive β=1.43 for a combined BO/VC dataset, but their method assumes that cumulative log project returns are normally distributed. However, the negative covariance between project returns and durations means that even if periodic project returns were symmetrically distributed, the cumulative returns would have a substantial left skew. Ang et al. note that their simulations show that their results are not robust to such a "hold-onto-losers" effect.

al. (2016) notes that the simple evaluation measures used by fund managers "raises questions as to whether limited partners understand the returns are leveraged". Consistent with this, we focus on a different question: how misleading are the IRRs reported by PE funds (and widely used by investors)?

The modified IRR (MIRR) has frequently been suggested as an alternative to the IRR, but fund managers seldom release their performance data in this form. Such MIRRs are sensitive to the level of returns which is assumed to be earned when early cash distributions are reinvested. If funds use different reinvestment assumptions, the resulting performance measures will not be comparable. Similarly, PMEs are only comparable if based on the same benchmark index. By contrast, the IRR and cash multiple are both derived directly from the fund's cashflows without the need for any judgmental inputs. This may make them seem more objective and unambiguous than the MIRR and PME, and this may help explain their continued popularity. However, whilst academics recommend alternative measures, IRRs are the only widely available estimates of PE funds' annualized returns, so investors have little choice but to use these as the basis for estimating the future returns they expect from PE.

Whatever the reasons, surveys clearly show that investors continue to rely on IRRs. Da Rin and Phalippou (2017) find that the IRR is the measure most frequently cited by investors as the most important criterion in their selection of PE funds. The cash multiple is less popular and is not in a form that can be directly compared to the returns on other asset classes. The survey by Gompers et al. (2016) finds that PE fund managers primarily use IRRs and multiples to evaluate potential projects (with over 60% using an IRR as their "most important benchmark") and that they believe that investors in their funds (the limited partners, LPs) generally rely on the same measures to assess fund performance. Brown et al. (2019) show that fund managers' previous IRRs affect their ability to attract commitments to future funds.

Some of the problems associated with IRRs have long been known. It is derived as the solution to a complex polynomial of discounted cash flows, so a set of cashflows may have multiple IRRs or none. Indeed, some argue that the IRR does not represent a rate of return, yet investors continue to use it as one (Phalippou, 2020). Indeed, the use of the IRR has been embedded into accepted reporting practice for PE funds.[3]

It is well known that a single early cash return can have a large impact on the IRR (e.g. Phalippou 2008, 2013). Indeed, large early cashflows back in the 1990s have kept some funds' since-inception IRRs at "an artificially sticky and high level" ever since (Phalippou, 2017).

[3] The CFA Guidance Statement on Private Equity (2012) stated that "the basic metric and industry practice used in measuring performance in the private equity industry is the since inception internal rate of return (SI-IRR)".

Funds have also been accused of deliberately manipulating their IRRs, e.g. by requiring portfolio companies to pay a dividend to the fund as soon as they have been acquired (Rabener, 2020), or funds' recent use of lines of credit to delay calling capital from their limited partners (Albertus and Denes, 2019, Schillinger et al., 2019). These can be regarded as ways in which funds deliberately use hidden increases in their leverage to boost their reported returns. Widespread use of these techniques would raise the returns on all PE projects. However, the biases we identify in this paper result instead from the variances and covariances of project returns and durations. These biases should thus be regarded as in addition to any increase in the IRR due to a hidden increase in leverage. Furthermore, the recent use of lines of credit is likely to have had very little effect on the historical datasets we use to estimate IRR biases.

Bond yields are, of course, also calculated as the IRR of their cashflows and are affected by the reinvestment problem: investors will only earn a holding period return equal to this IRR if they are able to reinvest the coupons they receive at the same rate. Unlike typical bond coupons, PE funds generate stochastic cashflows. Nevertheless, the reinvestment problem is often used as a catch-all explanation for PE fund IRRs: large early cash returns can generate high IRRs, which will be misleading if investors are unable to reinvest this cash at the same IRR. This explanation is not very useful because it is couched as a counterfactual: if investors were able to reinvest at the same rate as the IRR, then this IRR would be a perfectly good measure of returns.

By contrast, we explicitly model the size and timing of PE fund cashflows as stochastic processes and identify two biases generated by the observable statistical properties of these distributions. This approach allows us to quantify these biases using parametric methods and simulations. Specifically, we show that PE fund IRRs are biased because the timing of the cash distributions to investors is correlated with the returns achieved: high annualised returns are typically generated by projects which mature rapidly. We term this the Quit Whilst Ahead (QWA) bias, and demonstrate how it comes about and differs from the other problems with the IRR. We identify a separate convexity effect which also biases PE IRRs upwards compared to the returns on other asset classes.

We derive explicit expressions for these effects, showing (i) that they generate a systematic upward bias in PE fund IRRs; (ii) that these biases arise without any deliberate manipulation by fund managers, purely as a result of the innate characteristics of the distribution of PE cash returns; (iii) that alternative measures of annualised fund returns used by practitioners are similarly biased; (iv) that the PME is not itself biased, but it will become biased as soon as it is converted into an annualised return.

Our estimates show that these biases increase fund IRRs by an average of around 3% per annum. This is economically highly significant since it accounts for a substantial proportion of the 12.2% average net IRR generated by PE funds. Correcting for these biases is likely to remove the whole extent to which these IRRs appear to outperform the returns on listed equity indices such as the S&P500. Many investors now allocate substantial proportions of their portfolios to PE, and they do this on the basis of IRRs, which exaggerate the annualized returns achieved by PE. Failure to take account of the biases in these IRRs is thus likely to lead investors into badly misinformed strategic asset allocation decisions.

This analysis also contributes to three different parts of the existing literature: the literature on performance measurement, which investigates the extent to which popular performance measures are inherently biased or can be deliberately manipulated by the fund managers (e.g. Ingersoll et al., 2007); the wider empirical literature on bias in the returns reported by other types of fund managers (mutual funds (Elton, Gruber and Blake, 1996, Ter Horst, Nijman and Verbeek, 2001) and hedge funds, e.g. Baquero et al., 2005, and Fung and Hsieh, 2009), and the literature which explores how the IRRs reported for other asset classes differ from the other periodic returns (Dichev, 2007, Friesen and Sapp, 2007, Dichev and Yu, 2011).

The following section derives an expression for the QWA bias, and Section 4 uses this to generate a parametric estimate of this effect. Section 5 identifies an additional convexity bias which further increases fund IRRs. Sections 6 and 7 generate alternative simulation-based estimates which confirm the scale of these effects. Section 8 considers alternative performance measures that practitioners derive from fund IRRs and finds that these fail to remove these biases. Section 9 concludes.

2.3 The Quit-Whilst-Ahead Bias

The IRR is defined as the discount rate which sets the present value of the cash distributed to investors equal to the present value of the cash invested. This can be parametrized as an initial investment K_0, followed by a stream of cashflows d_t (which can be positive or negative) and a final end-of-horizon payment to investors K_T:

$$K_0 = \Sigma_{t=1}^{T} \frac{d_t}{(1+IRR)^t} + \frac{K_T}{(1+IRR)^t} \tag{1}$$

We can also express the fund value K_t at the end of each period as a function of organic growth r_t in the fund and any periodic returns of cash to investors (d_t):

$$K_t = K_{t-1}(1 + r_t) - d_t \tag{2}$$

Following Dichev and Yu (2011), we can substitute this into equation 1 to eliminate d_t, and rearrange to give:

$$IRR = \Sigma_{t=1}^{T} \frac{r_t K_{t-1}}{(1+IRR)^{t-1}} / \Sigma_{t=1}^{T} \frac{K_{t-1}}{(1+IRR)^{t-1}} \tag{3}$$

This shows that the IRR is a weighted average of the periodic returns r_t, where the relative weight given to each return is determined by the present value of the portfolio at the start of the period (discounted at the IRR). Thus the IRR is rightly referred to as the dollar-weighted return (although, more correctly, the weights are dollar present values).

The IRRs calculated for a number of asset classes have been found to be significantly lower than the corresponding time-weighted (geometric mean, GM) returns: for the US equity market (Dichev, 2007), mutual funds (Friesen and Sapp, 2007) and hedge funds (Dichev and Yu, 2011). In each case the comparatively low IRRs were interpreted as evidence that investor cash flows were badly timed, buying ahead of low returns and selling ahead of high returns. Hayley (2014) showed that such differentials could instead be caused by cashflows being correlated with past returns rather than future returns (e.g. "return chasing" as investors deliberately increase their exposure following unusually strong returns), and specifically that the differential between the GM returns and IRRs for aggregate US equity markets can be entirely explained by this retrospective bias, leaving no evidence of bad investor timing.

In this paper, we will demonstrate similar systematic biases in the IRRs calculated for PE funds. This context is very different since (i) the cash committed is fixed in advance, giving investors (the limited partners, LPs) no control over the timing of the cash flows over the life of the fund, so "return chasing" behaviour cannot be at work; (ii) the difficulty of valuing PE assets before they are liquidated means that the returns generated in each period by PE funds cannot be reliably measured. Thus, in contrast to previous time series analysis, the present paper investigates whether a bias is inherent in the cross-section of the separate projects that are undertaken by a PE fund.

2.3.1 Modelling the Cross-Section of Returns within a PE Fund

We model each PE fund as a collection of N individual projects. For simplicity, we assume that each project invests one dollar in period 0 and returns a single cash outflow to the investor at maturity T_i when the project is liquidated. Over its lifetime, each project generates cumulative log returns $\Sigma_{t=1}^{T} r_{it}$.

PE assets are illiquid and hard to value objectively before they are liquidated at T_i, so we observe only the cumulative return at maturity rather than individual periodic returns r_{it} within this. Nevertheless, we will model these cumulative returns as $\Sigma_{t=1}^{T} r_{it}$ in order to impose the condition that these returns r_{it} have a constant mean μ_r in all periods. This allows us to rule out any effect flowing from T_i to returns (for example, that projects which have already reached a given T_i tend subsequently to generate higher or lower returns than before). The relationship can instead be regarded as flowing entirely from r_{it} to T_i: unusually high periodic returns tend to be associated with relatively short maturities. This relationship can be thought of as a hazard rate effect: that high cumulative returns to date increase the probability that the project will mature in the next period, whilst the distribution of r_{it} remains iid across all projects and time periods.

We derive the present value of each project at the discount rate R:

$$PV_i = \frac{exp(\Sigma_{t=1}^{T_i} r_{it})}{exp(RT_i)} = exp(\Sigma_{t=1}^{T_i} r_{it} - RT_i) \tag{4}$$

Using $e^x \approx 1 + x + 0.5x^2$ as an approximation accurate for small ($\Sigma_{t=1}^{T_i} r_{it}$ -RT_i):

$$PV_i \approx 1 + (\Sigma_{t=1}^{T_i} r_{it} - RT_i) + \frac{1}{2}(\Sigma_{t=1}^{T_i} r_{it} - RT_i)^2 \tag{5}$$

If the fund invests in N such projects, the IRR is defined as the discount rate that gives zero NPV, implying that the PVs sum to the \$N initially invested:

$$N + \Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i} r_{it} - RT_i) + \frac{1}{2}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i} r_{it} - RT_i)^2 \approx N \tag{6}$$

$$\Longrightarrow \Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i} r_{it} - RT_i) + \frac{1}{2}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i} r_{it} - RT_i)^2 \approx 0 \tag{7}$$

We show below that these first and second-order terms each generate distinct biases in the IRR.

2.3.2 First Order Bias

In this section, we consider just the linear terms in equation (7), which approximate the IRR as a simple weighted average of the project returns:

$$\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i} r_{it} - RT_i) \approx 0 \tag{8}$$

We amend this to consider the excess returns in each period, where $\mu_r = \mathrm{E}[r_{it}]$:

$$\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it} - \mu_r) - (R - \mu_r)T_i) \approx 0 \tag{9}$$

$$\Longrightarrow R - \mu_r \approx \frac{\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i}(r_{it} - \mu_r)}{\Sigma_{i=1}^{N} T_i} \tag{10}$$

We separate the right-hand side into N separate ratios. For each one, we separate the denominator $\Sigma_{i=1}^{N} T_i$ into the lifetime of the project in the numerator T_i and the lifetimes of all other projects $T_{j \neq i}$. We then divide the top and bottom by $N\mu_T$, where μ_T is the population mean of T_i.

$$R - \mu_r \approx \Sigma_{i=1}^{N} \left(\frac{\Sigma_{t=1}^{T_i}(r_{it} - \mu_r)/N\mu_T}{\frac{\mu_T + \Sigma_{j=1}^{N-1, j\neq i} T_j}{N\mu_T} + \frac{T_i - \mu_T}{N\mu_T}} \right) \tag{11}$$

This makes the first term of the denominator approximately equal to 1, and $\frac{T_i - \mu_T}{N\mu_T}$ is likely to be small if N is large or var(T_i) small, allowing us to approximate using $\frac{1}{1+x} \approx$ 1-x:

$$\Longrightarrow R - \mu_r \approx \frac{1}{N\mu_T}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it} - \mu_r)) \left(\frac{\mu_T + \Sigma_{j=1}^{N-1, j\neq i} T_j}{N\mu_T} - \frac{T_i - \mu_T}{N\mu_T} \right) \tag{12}$$

Taking expectations: $\mathrm{E}[\Sigma_{t=1}^{T_i}(r_{it} - \mu_r)] = 0$, and the first fraction in the final term contains only terms in $T_j (j \neq i)$, which are independent of the terms in i. Hence:

$$E[R] - \mu_r \approx -\frac{1}{N^2\mu_T^2}\Sigma_{i=1}^{N}(E[(T_i - \mu_T)\Sigma_{t=1}^{T_i}(r_{it} - \mu_r)]) \tag{13}$$

$$E[R] \approx \mu_r - \frac{1}{N\mu_T^2} cov(T_i, \Sigma_{t=1}^{T_i}(r_{it} - \mu_r)) \tag{14}$$

Thus the IRR is a biased estimator of the mean periodic return μ_r if the cumulative excess return of each project covaries with its maturity. Figure 1 shows that this correlation is very strong: deals with the highest annualised returns may be liquidated within months, whereas less successful projects last much longer. This negative correlation biases the IRR upwards, so the average IRR will be greater than the average periodic returns μ_r achieved by the fund's projects.

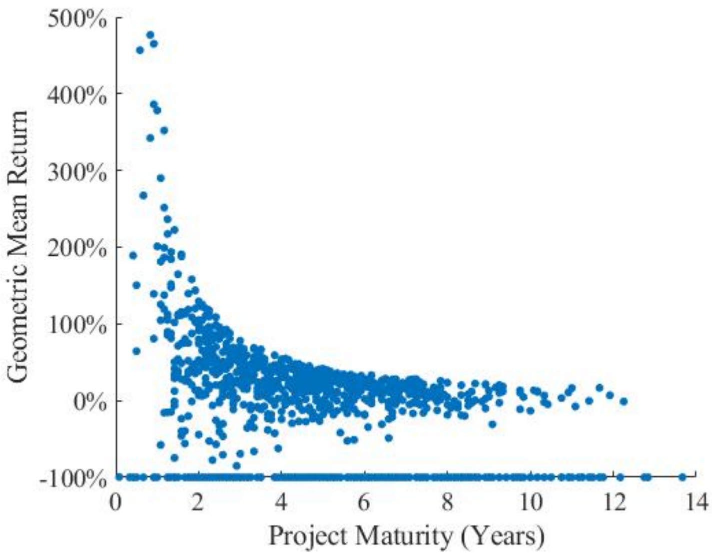

Figure 2.1: Durations And annualised Returns of PE Deals

Our derivation above modelled fund managers as picking projects randomly from the data shown in Figure 1 and assumed that they have no control over the size or timing of the cashflows that these projects subsequently generate for investors. Purely by good luck, some funds will find that an unusually high proportion of their initial investments generate high returns and these tend to have short lives. If the funds reinvested the cash from these successful projects into new projects picked from the same population, then these reinvestments should be expected to benefit from only an average amount of luck, so they would be likely to drag down the overall fund return. But funds do not reinvest: instead, they return the cash to their investors. This avoids diluting the lucky returns in their initial projects with less lucky subsequent projects. We term this the Quit-Whilst-Ahead (QWA) bias, and it will raise average fund IRRs purely as a result of the negative correlation shown in Figure 1: that shorter-duration funds tend to generate higher annual returns.

More formally, we saw that the IRR is (to a first-order approximation) simply an equally-weighted mean of the r_{it} of every project over the lifetimes of these projects $\frac{\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i} r_{it}}{\Sigma_{i=1}^{N} T_i}$. Taken at face value, this seems like a reasonable measure, but it is biased because $\Sigma_{i=1}^{N} T_i$ on the denominator is endogenous to the project returns in the numerator. Hence we have the following (where the covariance with this reciprocal is positive):

$$E[IRR] \approx E\left[\frac{\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i} r_{it}}{\Sigma_{i=1}^{N} T_i}\right] = E[\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i} r_{it}]E\left[\frac{1}{\Sigma_{i=1}^{N} T_i}\right] + cov(\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i} r_{it}, \frac{1}{\Sigma_{i=1}^{N} T_i}) \quad (15)$$

If one of the initial projects has an unusually short life T_i, this increases $1/\Sigma_{i=1}^{N} T_i$, so such projects are on average given greater weight in the IRR calculation than they would over a fixed horizon. Figure 1 shows that this covariance is strong.

This dynamic bias is distinct from and additional to other effects which have been shown to boost PE fund IRRs where funds (i) require portfolio companies to pay a dividend to the fund as soon as they have been acquired or (ii) use credit lines to delay calling cash from investors. These two effects are the result of deliberate behaviour by fund managers, which boosts the expected IRR by increasing fund leverage, and hence increasing the expected project return in each period (μ_r, in other words, $E[r_{it}]$). By contrast, our derivation above shows that the QWA bias boosts the expected IRR above μ_r. This bias is not caused by the deliberate behaviour of fund managers but it is inherent in the strong correlation observed in our dataset: projects with short durations tend to generate higher annual returns. In interpreting this QWA bias, we should note:

(a) It is a first-order effect. It results from the time period over which returns are calculated being endogenous to the returns achieved. It is distinct from the second-order effect that we identify in Section 5 below, which is instead due to the IRR being a non-linear function of the project lives.

(b) The bias is a function of the covariance of project returns and their durations, and Figure 1 shows exactly the situation which would lead to a large positive bias: returns and project lives both have high variance and are strongly negatively correlated. We estimate the size of this bias in the following sections using a range of different methods.

(c) This bias is not a risk-premium effect. It remains even if we set $\mu_r = 0$ in the derivation above.

(d) For simplicity, the derivation above used continuous-time discounting, but this is not vital: the same result can be obtained using discrete-time discounting (annually compounded returns are industry standard, e.g. under CFA GIPS), since this gives us the same first-order approximation.[4]

(e) QWA bias is declining in N: if a fund contains many projects, then an individual project with high r_i and low T_i will have little effect on $\Sigma_{i=1}^{N} T_i$ and hence little effect on the weight that this project is given in the IRR calculation, resulting in little bias.

(f) Conversely, this bias should not be presumed to be a short period (small T) effect, despite the $1/N\mu_T^2$ in equation (14). Suppose that the relationship between project returns and their durations is linear: $T_i = k\Sigma_{t=1}^{t=T_i}(r_{it} - \mu_r) + \mu_t + \epsilon_i$ (where $\mu_r = E[r_{it}]$ and $\mu_t = E[T_i]$). Substituting this into our expression for the bias:

$$\text{QWA Bias} \approx -\frac{1}{N\mu_T^2} cov(T_i, \Sigma_{t=1}^{T_i}(r_{it} - \mu_r)) \tag{16}$$

$$\approx -\frac{1}{N\mu_T^2} cov(k\Sigma_{t=1}^{t=T_i}(r_{it} - \mu_r) + \mu_t + \epsilon_i, \Sigma_{t=1}^{T_i}(r_{it} - \mu_r)) \tag{17}$$

$$\approx -\frac{k}{N\mu_T^2} var(\text{cumulative excess return}) \tag{18}$$

If each periodic return r_{it} is iid, then the variance of the cumulative excess return will be proportional to T_i. Hence we would expect the bias to be proportional to $\frac{1}{N\mu_T}$. However this assumes that $\sigma_{T_i}^2$ does not vary with μ_T. If instead the proportionate variation in T_i is the same in populations with differing μ_T, then $\sigma_{T_i}^2$ will be proportional to μ_T, and the bias will be invariant to μ_T. Thus we should not assume that the QWA bias is a short-horizon effect that shrinks as average project lives increase.

2.4 Quantifying the QWA Bias

Our starting point in quantifying the QWA bias is simply to evaluate the expression derived above. However, a number of simplifying assumptions were used in its derivation, and the extreme volatility exhibited by PE project returns means that these may well be imprecise. Hence, for robustness, we will also use a range of different simulation techniques to estimate the biases by comparing the IRRs of simulated funds with corresponding bias-free return measures (Sections 6-7 below).

[4] Discrete period discounting gives $PV_i = \frac{e^{\Sigma_{t=1}^{t=T_i} r_{it}}}{(1+R)_0^{T_i}}$. Setting ΣPV_i = N gives us the same first-order approximation $\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i} r_{it} - \Sigma_{i=1}^{N} T_i R) = 0$ as above, and hence R $\approx \frac{\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i} r_{it}}{\Sigma_{i=1}^{N} T_i}$

2.4.1 Data on Private Equity Projects

We use the PE deal exits database from MergerMarket comprising 1,585 investment exits by 438 PE funds with purchase years from 1998 to 2018. The collected data is limited to the transaction dates, percentage of the target company equity bought or sold, and transaction values.

This database has several issues that need to be taken into account. First, it includes buyout (BO) and venture capital (VC) deals, with no way to distinguish them from each other. However, Brown et al. (2020) show a very similar relationship to Figure 1, using an entirely different dataset comprising only BO projects. This confirms that the covariance between project durations and annualised returns is strongly negative within a population of BO projects, rather than being due to any additional heterogeneity in our dataset due to the inclusion of both VC and BO.

Second, if the purchased company is sold in multiple transactions, the database contains information on only the final tranche sold. In 63% of deals the whole of the acquired equity was sold in a single transaction, so the exit information for these deals is complete. For the remainder, we have information on the final tranche of equity, but not on earlier partial sales of equity in these firms. Our central estimates include the returns generated on these partial sales with the initial investment cost scaled down to reflect the cost of the proportion subsequently sold, on the assumption that they are representative of the whole exit transaction. For robustness, we also calculated our results using only the 63% of deals which exited in one transaction. This resulted in very similar estimates for the QWA bias.

Third, the database does not provide information regarding the financing of the deals, and, as these are mostly private companies, it is not possible to obtain this information from other sources. The IRR measures the return on the equity that the fund invests, so we are forced to make an assumption about the leverage involved. For robustness, we have confirmed that our bias estimates are positive and economically significant over a wide range of parameter assumptions. Our central assumptions are a leverage ratio of 60% (the average reported by S&P Global Market Intelligence, and close to the levels reported by Metrick and Yasuda, 2010, and Axelson et al., 2013), and an interest rate of 7.5% (consistent with the Libor + 4.9% reported by Axelson et al., 2013).

In common with other research in this field, we filter out projects in each financing scenario which show cash multiples greater than 6 or annualised returns greater than 500%. We confirm that on the basis of these assumptions our simulations generate a distribution of fund IRRs which is similar to those reported in other databases. For robustness, we also confirm that the observed covariance of project returns and durations was not generated by filtering out outliers with exceptional cash multiples, but remains substantial and negative with alternative filters or with no filtering of multiples. Indeed, our filtering assumptions are conservative since they reduce the observed covariance.

Table 1 records the key features of the distribution of project returns generated by the Mergermarket data once we have applied the leverage, interest rate and other assumptions discussed above, and compares these with the corresponding data reported in other studies. Our assumptions generate realistic proportions of deals with negative returns, although overall our data turns out to be slightly worse-performing, with higher percentages of bankrupt deals and a lower median project multiple and median annualised return. The MergerMarket database only includes data for companies that were sold as going concerns. It excludes failing companies whose assets were sold separately. These are likely to record below-average returns but our estimates of the QWA bias will not be sensitive to the level of these returns - only to their covariance with T_i. The exclusion of these failed deals leaves us with a more homogeneous dataset. If anything this is likely to make our bias estimates more conservative, by removing the possibility that this additional heterogeneity tended to increase the observed covariance.

Metrics	Previous Studies	Our Data
Negative returns %	30 - 40%	38.0%
Bankrupt Deal %	17 - 20%	22.9%
Median Multiple	1.90 - 2.10	1.77
Median Annualised Return	21.0%	14.5%
Median Months Held	51.6 - 60.0	52.0

Table 2.1: Deal Returns and Durations

This table compares the return and duration-related characteristics of the private equity deals included in the Mergermarket dataset used in this study with the ranges reported by previous academic studies. The studies used as benchmarks are Lopez-de-Silanes et al. (2015), Hüther (2016) and Braun et al. (2017). Each project return is calculated from a single cash investment and a single cash distribution, so the returns referred to here are annualised geometric mean (GM) returns.

Funds report their IRRs net of fees, and these fees are calculated as a function of overall fund performance. For this reason, project data is only available before fees are deducted. To simulate net fund IRRs we are forced to model this fee structure explicitly. We find that the leverage assumptions described above result in a distribution of simulated net fund IRRs which closely matches empirical data reported in other databases (Figure 3 below). We could instead fine-tune our leverage assumptions to more closely match the gross returns reported in Table 1 for other sources, and then adjust our assumed fee structure so that the resulting net fund IRRs continue to match those reported elsewhere. However, the basic parameters of the fee structure are well documented, so adjusting these would itself be unrealistic. For robustness we use a range of different estimation techniques, but our key objective is to estimate the biases that are inherent in the net IRRs reported by PE funds. For these reasons our preferred approach is to use gross data that are an adequately close - if not exact - empirical match, apply a fee structure with well-known parameters, and then confirm that the resulting distribution of net fund IRRs closely matches other sources. As a further check, in Sections 6 and 7 we derive estimates of very similar size using (i) simulations based on the MergerMarket project data, thus avoiding the inevitable simplifications that come with parametrizing this data; (ii) simulations using an entirely separate database of net fund cashflows.

2.4.2 Parametric Estimates of IRR biases

Our starting point is to evaluate the expression derived above: QWA Bias $\approx -\frac{1}{N\mu_T^2}cov(T_i, \Sigma_{t=1}^{T_i}(r_{it} - \mu_r))$. The projects in our data have an average maturity of 4.3 years, and the covariance between these maturities and the cumulative abnormal return $\Sigma_{t=1}^{t=T_i}(r_{it} - \mu_r)$ is -2.3. The first row of Table 2 evaluates this expression for different numbers of projects per fund (N).

	Number of Deals Per Fund								
Panel A: Full Dataset	1	2	3	4	5	6	9	12	All
Bias derived from sample covariance	12.5%	6.2%	4.2%	3.1%	2.5%	2.1%	1.4%	1.0%	0.0%
Sum(R_iT_i)/Sum(T_i)	35.5%%	26.4%	24.1%	22.9%	22.3%	22.7%	21.8%	21.4%	20.7%
Implied Bias	14.8%	5.7%	3.4%	2.2%	1.6%	1.9%	1.1%	0.7%	0.0%
Panel B: Robustness	1	2	3	4	5	6	9	12	All
Bias derived from sample covariance	10.3%	5.1%	3.4%	2.6%	2.1%	1.7%	1.1%	0.9%	0.0%
Sum(R_iT_i)/Sum(T_i)	37.5%%	30.2%	27.2%	26.3%	25.8%	25.6%	25.4%	25.1%	24.5%
Implied Bias	13.1%	5.7%	2.7%	1.8%	1.3%	1.1%	0.9%	0.6%	0.0%

Table 2.2: Parametric Estimates of QWA Bias

This table provides parametric estimates for the Quit-Whilst-Ahead Bias. Columns represent the number of deals made by a private equity fund, "All" representing a fund entering into all available deals in the database. Panel A uses the complete Mergermarket dataset on private equity deals, while Panel B eliminates the deals with maturity over 7.5 years. The first line calculates the bias parametrically, based on the derived bias formula: QWA Bias $\approx -\frac{1}{N\mu_T^2}cov(T_i, \Sigma_{t=1}^{T_i}(r_{it} - \mu_r))$. The second line calculates IRR for varying N's using the derived IRR approximation: $\Sigma_{i=1}^{N} r_i T_i / \Sigma_{i=1}^{N} T_i$. The third line calculates the bias as the difference between the IRR with N deals and All deals.

These positive estimates represent the degree to which fund annualised IRRs are increased by QWA bias. It is intuitive that these estimates are declining in N, since if each project accounts for only a very small proportion of fund value then the endogeneity which causes the bias will be correspondingly slight. Jenkinson, Kim and Weisbach (2021) report that the median buyout fund invests in nine projects, but our derivation above assumed that projects all invest equal amounts and that returns are independent across projects. These assumptions represent ideal diversification, whereas in practice some projects are much larger than others and systematic and sectoral risk factors may lead to significant covariance across project returns. This will increase the QWA bias, since funds will in effect behave as if they were composed of a smaller number N of truly independent projects (or, equivalently, a smaller number of independent principal components). Thus setting N=9 would underestimate the likely degree of QWA bias. A simple way to correct this is to reduce our assumption for N. On the other hand, these estimates are based on the covariance of gross project returns, and the option-like structure of fund fees means that the variance of net cashflows should be expected to be slightly lower. Taking both these factors into account, we argue below that N=6 is the most appropriate assumption (implying QWA bias of +2.1%), since this matches the observed variance in empirical net fund IRRs

Our derivation above used the approximation $1/(1 + x) \approx 1 - x$, which in this context could be inaccurate for small N. To avoid this we return to our earlier approximation IRR $\approx \Sigma_{i=1}^{N} r_i T_i / \Sigma_{i=1}^{N} T_i$. The second row of Table 2 shows that this decreases as we sum over progressively larger N, consistent with decreasing QWA bias. The estimate which includes all 732 projects in our sample represents a massively diversified fund which will have minimal QWA bias. Differences between this and the corresponding figures for smaller N represent the amount of the bias for these more concentrated portfolios. This generates QWA estimates similar to those above. Specifically, for N=6 we obtain a bias estimate of 1.9% per annum.[5]

As described above, we already excluded extreme outliers from our dataset. As a further robustness check, we removed all projects which recorded maturities greater than 7.5 years (a further 9% of our dataset). The results are shown in the second panel of Table 2. Even on this artificially conservative basis, our estimates of QWA bias remain economically significant. This is reassuring in showing that the effect is not simply the result of a few extreme observations. However, the QWA bias is a covariance effect, so our estimates will inevitably be sensitive to outliers in the distribution of project returns and maturities, and artificially reducing the observed variation in our dataset will inevitably underestimate the QWA effect. Finally, note that our simulation-based estimates in sections 6 and 7 remove the need for any assumptions about parametrization and generate slightly larger bias estimates than the parametric estimates above.

Biases of the magnitudes estimated above would be economically highly significant, given

[5]This estimate is based on the annually-compounded project returns in our database, since this is consistent with the fact that funds report annually-compounded IRRs. Replacing these with the corresponding continuously compounded (logarithmic) returns would artificially shrink the right tail of the return distribution, but even under this extremely conservative manipulation of the data, our estimated QWA bias remains economically highly significant at 1.3% per annum.

that the average net IRR recorded by PE funds has been 12.2% per annum (see Table 4, below). In choosing their strategic asset allocations, investors are likely to compare this figure to the return they expect on other assets. Pension funds generally assume a total asset return of 8% per annum, and this includes significant holdings of comparatively low-risk bonds, so the implied expected return on equities must be higher. A total equity return of around 10% would be consistent with the observed long-term geometric mean total return on the S&P500 index (investors who mistakenly use the arithmetic mean S&P500 index as a comparison would derive a larger figure). We cannot pin down investor expectations with any great precision, but these simple comparisons suggest that QWA bias in these IRRs could on its own account for most, if not all, of the amount by which average PE IRRs appear to outperform the return on listed equities.

Furthermore, the estimates above are for only the first-order "Quit Whilst Ahead" bias resulting from the covariance of project returns and maturities. In the following section, we demonstrate the existence of an additional second-order bias resulting directly from the variance of project lives T_i. In subsequent sections, we use a variety of simulation techniques to generate non-parametric estimates which include all biases.

2.5 Second-Order (Convexity) Bias

The figures derived above are estimates of the QWA bias, which is derived from the first-order term of the Taylor expansion of the expression which defines the IRR. In this section, we demonstrate that there is an additional second-order bias that further increases fund IRRs. We use the same framework as above, but this time consider both terms in equation (7):

$$\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i}(r_{it}-R)+\frac{1}{2}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R))^2\approx 0 \tag{19}$$

Decomposing the first order term, as before:

$$(R-\mu_r)\Sigma_{i=1}^{N}T_i\approx\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i}(r_{it}-\mu_r)+\frac{1}{2}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R))^2 \tag{20}$$

Separating $\Sigma_{i=1}^{N}T_i$ into T_i and the lifetimes of all other projects $\Sigma_{j=1}^{N-1,j\neq i}T_j$, then dividing top and bottom by $N\mu_T$:

$$R-\mu_r\approx\Sigma_{i=1}^{N}\left(\frac{\Sigma_{t=1}^{T_i}(r_{it}-\mu_r)/N\mu_T}{\frac{\mu_T+\Sigma_{j=1}^{N-1,j\neq i}T_j}{N\mu_T}+\frac{T_i-\mu_T}{N\mu_T}}\right)+\frac{1}{2}\Sigma_{i=1}^{N}\left(\frac{(\Sigma_{t=1}^{T_i}(r_{it}-R))^2/N\mu_T}{\frac{\mu_T+\Sigma_{j=1}^{N-1,j\neq i}T_j}{N\mu_T}+\frac{T_i-\mu_T}{N\mu_T}}\right) \tag{21}$$

Noting that $\frac{\mu_T + \Sigma_{j=1}^{N-1, j\neq i} T_j}{N\mu_T} \approx 1$, we approximate using $1/(1+x) \approx 1 - x + x^2$, where x = $\frac{T_i - \mu_T}{N\mu_T}$.

$$\text{R - } \mu_r \approx \frac{1}{N\mu_T}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-\mu_r))\left(1 - \frac{T_i-\mu_T}{N\mu_T} + \left(\frac{T_i-\mu_T}{N\mu_T}\right)^2\right) + \frac{1}{2N\mu_T}\Sigma_{i=1}^{N}\left(\left(\Sigma_{t=1}^{T_i}(r_{it}-R)\right)^2\left(1 - \frac{T_i-\mu_T}{N\mu_T} + \left(\frac{T_i-\mu_T}{N\mu_T}\right)^2\right)\right) \quad (22)$$

We first consider the special case where all projects are realised at a fixed horizon $T_i = \mu_T = T^*$, noting that $E[\Sigma_{t=1}^{T_i}(r_{it} - \mu_r)] = 0$:

$$E[R] \approx \mu_r + \frac{1}{2NT^*}E[\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T^*}(r_{it} - R))^2] \quad (23)$$

We saw above that R is (to a first-order approximation) simply the sample mean of all the periodic returns r_{it}. Hence, we can interpret the quadratic term as the variance of these returns around their own sample mean. This has expectation $\frac{(N-1)\sigma_r^2}{N}$.

$$E[R] \approx \mu_r + \frac{(N-1)\sigma_r^2}{2N} \quad (24)$$

This equation shows the "diversification return" by which the geometric mean (GM) return on a portfolio of N iid assets is raised above μ_r (the expected GM return on a single one of these assets). This requires careful interpretation. First, we note that the IRR of a portfolio of assets with identical maturities $T_i = T^*$ is simply the GM return.[6] Thus this effect is not specific to the IRRs that are the focus of this paper. It is relevant whenever we compare the GM returns of different assets or portfolios.

This effect can be regarded as simply an application of the well-known relationship between the geometric and arithmetic means: E[GM] = E[AM] - $\sigma_r^2/2$. This relationship comes about because the GM return is a concave function of the final portfolio value: GM = $(K_T/K_0)^{1/T} - 1$ in discrete time (or GM = $\frac{1}{T}log(K_T/K_0)$ in continuous time). For example, if the distribution of asset returns is symmetrical, then the concavity of this function generates an upward skew in the corresponding distribution of terminal asset values because compounding a slightly above-mean return $\mu + d$ increases the terminal value by more than a below-mean return $\mu - d$ would reduce it. This upward skew boosts the expected terminal value of each asset by $\sigma_{r_i}^2/2$, as can be seen in the textbook result that the mean of a lognormal distribution with mean return μ and variance $\sigma_{r_i}^2$ is $e^{\mu+\sigma_{r_i}^2/2}$, but its median is e^{μ}.

We reverse the process when we calculate the GM returns corresponding to these asset

[6] The GM is derived from the ratio of the final portfolio value to its initial value: GM = $\left(\frac{\Sigma_{i=1}^{N} K_{iT*}}{\Sigma_{i=1}^{N} K_{i0}}\right)^{1/T}$ - 1 $\implies \frac{\Sigma_{i=1}^{N} K_{iT*}}{(1+GM)^T}$ - $\Sigma_{i=1}^{N} K_{i0} = 0$. The latter expression states that the NPV of the portfolio is zero at the discount rate GM, which is the definition of the IRR. Hence the IRR and GM are identical when all assets have equal maturity.

values: the upward skew disappears as the curvature of the return function punishes positive outliers with particularly large K_T, thus reducing the mean return by $-\sigma_{r_i}^2/2$. This effect has been termed "volatility drag".

However, these two effects no longer cancel out when we consider a portfolio of assets. The concavity of the return function: (i) gives an upward skew to the distribution of final values which increases the expected value of each asset by half its variance; (ii) reduces the expected return corresponding to this total final value by half of the variance of the portfolio. Thus for a portfolio of N iid assets, the expected final portfolio value is boosted by $\sigma_{r_i}^2/2$ but the portfolio return associated with this distribution is reduced by $\sigma_{r_i}^2/2N$. The expected portfolio return is the expected asset return plus $\frac{\sigma_{r_i}^2}{2}(1-\frac{1}{N})$, as shown in equation (23) above.

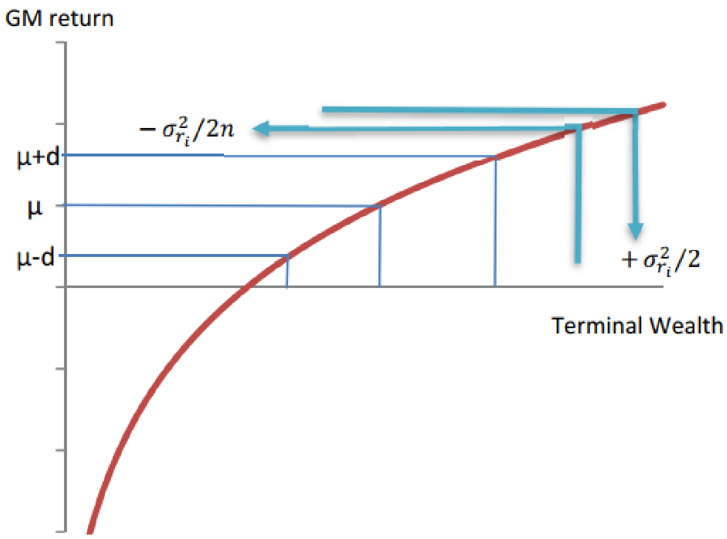

Figure 2.2: Illustration of Volatility Drag and "Diversification Return"

If we are comparing portfolios with similar levels of diversification and containing assets with similar variances, then the GM returns of these portfolios would give a like-for-like comparison. But with different levels of diversification returns, these GMs give a misleading comparison. For example, a particularly highly diversified mutual fund will, all else equal, tend to record a higher GM return than other funds which invest with equal skill in a smaller number of similar assets. This differential may be misinterpreted as outperformance by the better-diversified fund. Portfolio diversification is obviously desirable, but investors do not need to invest in highly diversified funds to achieve this ; they can instead invest in a highly diversified selection of less diversified funds. Comparing GM returns may thus encourage investors to choose inappropriate funds. Cuthbertson et al. (2016) showed that confusion about this "diversification return" has led to dynamic trading strategies being recommended, which have no impact on the expected terminal value of the portfolio but merely boost the GM return by reducing volatility drag.

This issue is of much wider scope than the PE IRRs that are our focus in this paper. However, we need to take it into account since our goal here is to identify any additional biases which affect the IRRs of PE funds when compared to the GM returns calculated for more liquid assets such as exchange-traded equities. Phalippou (2020) reports that PE fund managers do indeed cite the GM returns on other asset classes as benchmarks against which their fund IRRs should be compared.

Our assumption above that all projects are realised at a fixed horizon T^* made the fund IRR identical to the GM return. Relaxing this assumption shows how variation in T_i affects the IRR. In the slightly more general case where T_i varies but is not correlated with either r_{it} or $(\Sigma_{t=1}^{T_i}(r_{it} - R))^2$, most of the terms in equation (22) have zero expectation (since terms in $T_{j(j \neq i)}$ are independent of the terms in i and $E[r_{it} - \mu_r] = 0$, but the second order product term does not:

$$E[R] \approx \mu_r + \frac{1}{2N\mu_T}\Sigma_{i=1}^{N} E[(\Sigma_{t=1}^{T_i}(r_{it} - R))^2] E\left[1 + \left(\frac{T_i - \mu_T}{N\mu_T}\right)^2\right] \tag{25}$$

$$\approx \mu_r + \frac{(N-1)\sigma_r^2}{2N}\left(1 + \frac{\sigma_t^2}{N\mu_T}\right) \tag{26}$$

Thus, even in the absence of the covariance which generates QWA bias, the variance of T_i increases the expected IRR. Our dataset shows that these project maturities vary widely, with a mean of 4.3 years but a standard deviation of 2.3 years. However, before using this expression to quantify this effect, we should recall that it is based on the approximation $1/(1+x) \approx 1-x+x^2$, which is adequate to demonstrate the existence of this effect, but may be a poor approximation, since the higher order terms in this Taylor series could also be significant. In particular, the distribution of project maturities T_i is positively skewed, with fewer of the extremely short durations which would maximise this convexity effect. Furthermore, shorter maturity projects record more volatile annualised returns than longer projects (see Figure 1), and this negative correlation will reduce the positive skew in the resulting distribution of terminal values. Hence the positive effect on the expected IRR is likely to be smaller than the $1 + \frac{\sigma_t^2}{N\mu_T}$ derived above. To avoid an inappropriate approximation, we recall that this effect comes about because we derived our expression for the expected IRR by dividing both sides of equation (20) by $\Sigma_{i=1}^{N} T_i$:

$$(R-\mu_r) \approx \frac{\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_i}(r_{it}-\mu_r)}{\Sigma_{i=1}^{N}T_i} + \frac{\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R))^2}{2\Sigma_{i=1}^{N}T_i} \tag{27}$$

If $\Sigma_{i=1}^{N}T_i$ is correlated with the cumulative returns, then we have QWA bias. If there is no such correlation, then the linear term on the right has zero expectation, leaving:

$$E[R-\mu_r] \approx E\left[\frac{\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R))^2}{2\Sigma_{i=1}^{N}T_i}\right] = \frac{1}{2}E\left[\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R))^2\right]E\left[\frac{1}{\Sigma_{i=1}^{N}T_i}\right] \tag{28}$$

When T_i is fixed at $T_i = \mu_T = T^*$, this simply becomes $\frac{1}{2NT^*}E\left[\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R))^2\right]$ giving us the expression above for the diversification return for the portfolio geometric mean return calculated over a fixed horizon. But when T_i varies independently of returns, this boosts the diversification return simply because the reciprocal is a convex function such that $E\left[\frac{1}{\Sigma_{i=1}^{N}T_i}\right] > \frac{1}{E[\Sigma_{i=1}^{N}T_i]}$ (given that T_i>0). Our data on project returns shows that for N=6, the left-hand side of this inequality is 5% larger than the right, so independent variance in $T_i$in our dataset should be expected to boost the diversification return to 7.05% from its original 6.71%. (derived by evaluating $\frac{(N-1)\sigma_r^2}{2N}$ using the observed 16.1% maturity-weighted variance of project returns). This represents a more modest increase (+0.34%) in the expected IRR than the QWA bias discussed above, but: (i) it represents an entirely separate effect, which will arise even in the absence of QWA bias; (ii) it should be considered a bias since it boosts the IRRs recorded for portfolios of assets with varying T_i above those (GMs) of portfolios with entirely similar return characteristics but a fixed horizon.

2.6 Simulation Estimates of the Biases

The parametric bias estimates derived above were based on a number of assumptions. We now turn to simulation techniques as an alternative. These avoid the simplifications that are inherent in parametrizing the data. Furthermore, our estimates above were for only the first and second-order biases, whereas simulations will also include any higher-order effects.

We demonstrated that QWA bias and convexity bias both arise because of variations in the maturities (T_i) of the projects in which PE funds invest, either directly (convexity bias) or because they are correlated with project returns (QWA bias). Both biases will be absent in a strategy which invests in PE over an exogenously fixed horizon, immediately re-investing any early cash distributions into similar PE investments. Comparing simulated fund IRRs (without reinvestment) with the simulated returns of funds which reinvest in similar projects over a fixed horizon will thus give us an estimate of the combined effect of QWA and convexity biases.

To confirm this intuition, we again assume each PE fund comprises N projects which each invest \$1, generate periodic returns r_{it} and mature at time T_i. Now we assume that the cash released by these projects at maturity is reinvested at a rate R^* until a fixed horizon T^*, at which point their terminal values are measured. Discounting these terminal values at discount rate R gives: $\Sigma_{i=1}^{N} NPV_i = \Sigma_{i=1}^{N}\left(e^{\Sigma_{t=1}^{T_i}(r_{it}-R)+\Sigma_{t=T_i}^{T^*}(R^*-R)} - 1\right) = 0$ as the expression which defines R=IRR. Consider the first two terms in the Taylor expansion of this exponential function:

$$\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R)+\Sigma_{t=T_i}^{T^*}(R^*-R)) + \frac{1}{2}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R)+\Sigma_{t=T_i}^{T^*}(R^*-R))^2 \approx 0 \quad (29)$$

We decompose the first term, substituting: $\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R)+\Sigma_{t=T_i}^{T^*}(R^*-R)) = \Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-\mu_r)+\Sigma_{t=T_i}^{T^*}(R^*-\mu_r)-NT^*(R-\mu_r))$, where $\mu_r = E[r_{it}]$. Back in section 3.2, when we reached this stage in the derivation of the IRR, we found that obtaining a first-order solution for R required us to divide by ΣT_i (see equation 10). This gave rise to the QWA bias because the ΣT_i in the denominator covaries with the project returns in the numerator. This time we are dividing by an exogenous NT^*, so the IRR calculated over this fixed horizon does not suffer from QWA bias:

$$R \approx \mu_r + \frac{1}{NT^*}\left(\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-\mu_r)+\Sigma_{t=T_i}^{T^*}(R^*-\mu_r)) + \frac{1}{2}\Sigma_{i=1}^{N}(\Sigma_{t=1}^{T_i}(r_{it}-R)+\Sigma_{t=T_i}^{T^*}(R^*-R))^2\right) \quad (30)$$

We saw earlier that convexity bias is a function of the variance of the project maturities T_i, so this will be zero when the IRR is calculated over a fixed horizon. The IRRs calculated without reinvestment suffer from both QWA and convexity biases, but equivalent IRRs calculated with reinvestment to a fixed horizon suffer neither. Thus the difference between the IRR and the return on a corresponding fixed-horizon strategy can be used to estimate the size of the biases inherent in the IRR.

It is worth noting that the total return indices calculated for other assets similarly assume that all cash distributions (such as dividends or coupons) are immediately reinvested into the same asset. Using the same approach for PE will ensure a like-for-like comparison with these other assets. Such reinvestment means there are no intermediate cashflows, so, as we saw in the previous section, the IRR becomes identical to the geometric mean return.

Such fixed-horizon reinvestment strategies could be modelled using either fixed or stochastic returns during the reinvestment period. For robustness, we take both approaches in the following sections.

2.6.1 Fixed Rate Reinvestment

The most obvious way to model fixed-horizon returns is to calculate the modified IRR (MIRR) which assumes that a steady rate of interest is earnt on any cash returned to investors before the end of the time horizon. The textbook approach is to calculate the MIRR using the risk-free interest rate (typically proxied as the yield on short-term government bonds). This is likely to be very low compared to the returns expected on PE investments. The MIRR calculated on this assumption would represent the return on a dynamic strategy which shifts from a high-risk asset (PE) into cash over the course of the investor's horizon. It is not clear why investors would choose such a strategy, so although it is an investible strategy, we have no reason to think that it represents a sensible benchmark. Choosing such an inappropriate reinvestment rate would understate the expected returns that should be expected from maintaining an exposure to PE. Larocque et al. (2022) compare fund IRRs with the "multiple return" calculated from the fund's cash multiple and lifetime as $MOIC^{1/T} - 1$, but this is simply the MIRR calculated with a reinvestment rate of zero. Under this extreme assumption, they find that the mean fund IRR exceeds the mean multiple return by almost 8% per annum.

Phalippou (2008) instead suggested using a fixed reinvestment rate of 8% (a figure commonly used as the hurdle rate used in calculating fund performance fees) or the total return on a popular listed equity index such as the S&P500. However, these may still be excessively low if PE funds earn additional risk premia, such as those resulting from a CAPM beta greater than unity, an illiquidity premium (as was identified by Franzoni et al., 2012) or a small capitalisation equity premium (e.g. Jegadeesh, Kraussl and Pollet, 2015).

The project returns in our dataset incorporate any such risk premia. The weighted average of the annualised discrete time gross GM returns achieved by each project in our dataset (weighted by their lifetimes (T_i) and gross of fees) is 20.7% per annum. This represents a first-order approximation of the average return that would be achieved if we invested sequentially in projects picked at random from this dataset (the T_i-weighting reflects the fact that the probability that at any given moment we are invested in a high-return project is relatively low because such projects tend to have short lives). This figure incorporates no QWA bias because it measures the return on a strategy which involves no early returns of cash (hence no "quitting").

However, using this figure would lead to misleadingly low MIRRs because this return is constant and so will not generate the diversification return seen on the stochastic returns on the initial investments. To show this, we return to equation (30) and set our reinvestment rate equal to the mean periodic return $R^* = \mu_r = E[r_{it}]$. Taking expectations:

$$E[R] \approx \mu_r + \frac{1}{2T^*} E\left[(\Sigma_{t=1}^{T_i}(r_{it} - R) + \Sigma_{t=T_i}^{T^*}(R^* - R))^2 \right] \tag{31}$$

We saw in Section 3.2 that to a first-order approximation, the IRR is the sample mean of the periodic returns r_{it}, so the cross-product above has approximately zero expectation:

$$\approx \mu_r + \frac{1}{2T^*} E\left[(\Sigma_{t=1}^{T_i}(r_{it} - R))^2 \right] + \frac{1}{2T^*} E\left[(\Sigma_{t=T_i}^{T^*}(R^* - R))^2 \right] \tag{32}$$

The first quadratic term is half the variance of these returns around their sample mean $(= \frac{N-1}{2N} T_i \sigma_r^2)$. As we saw earlier, this is the diversification return caused by the variance of the returns on the initial investment projects. However, the second expectation term is much smaller: it is half the variance of this sample mean R around μ $(= \frac{1}{2N}(T^* - T_i)\sigma_r^2)$. Thus using a fixed reinvestment rate which does not correct for this diversification return will lead to MIRRs which are systematically lower than the corresponding IRRs. This reduction should not be regarded as the correction of a bias since the diversification return represents the increase in the mean terminal wealth due to the upward skew caused by compounding: an effect of genuine value to investors. To ensure that our MIRR is a like-for-like comparison with the returns calculated on stochastic assets held throughout the investment horizon, we should either (i) use a fixed reinvestment rate comprising: the risk-free rate + appropriate risk premia + $\frac{N-2}{2N}\sigma_r^2$ to compensate for the missing diversification return (we take this approach here); or (ii) use stochastic reinvestment returns with appropriate mean and variance (we simulate these in Section 7).

To derive reinvestment rates which include an appropriate diversification return, we consider the 30.4% gross IRR generated by a portfolio which invests equally in every project in our database. This IRR includes minimal QWA and convexity biases (since these both fall with 1/N, and our dataset includes hundreds of projects) but does include diversification return. By contrast, the 20.7% T_i-weighted average project GM return contains no diversification return or convexity bias (since it is the average of single-project returns, and for N=1, these effects are both zero). The difference between these two returns thus represents the maximum possible diversification return for a large N portfolio. For smaller portfolios, we include a fraction $\frac{N-2}{2N}$ of this additional return. Table 3 compares (i) the mean IRR for funds, each containing N randomly-selected projects from our dataset; with (ii) the corresponding MIRR that would result if early returns of cash from these projects were reinvested at a constant return. These

IRRs and MIRRs include the same risk premia and equivalent levels of diversification return (increasing in N as diversification improves). Still, the IRRs will be boosted by QWA and convexity biases, whilst the MIRRs will not. The difference between these figures represents the combined size of these two biases.

The choice of time horizon is also important. The conventional approach would be to choose a horizon at least as long as the longest project. However, this would make our estimates very sensitive to any error in the reinvestment rate used: an excessively low rate would reduce the MIRRs and overestimate the biases. We also modelled returns over a very short horizon of three years. Many projects will mature after this horizon, so rather than reinvesting, the MIRR calculation discounts project terminal values back to the equivalent PV at the three-year horizon. An excessively low reinvestment (discount) rate would thus overstate the MIRRs and understate the biases. We can observe this effect in Table 3, where for our central case N=6: a 7.5-year horizon with our lower reinvestment rate (20.7%) generates lower MIRRs than with the higher (30.4%) rate, and hence a higher bias estimate. Using the 3-year horizon, this difference is reversed since these reinvestment rates will frequently be discount rates, and a lower discount rate applied to future project liquidation values boosts the MIRR, implying lower bias. Our central estimates are based on a horizon of 4.3 years. This is the mean project life, so using this horizon implies that there will be as much discounting back as reinvesting, implying that the average MIRRs calculated over this horizon should be least sensitive to the possibility that we are using an inappropriate reinvestment rate. For this reason, we consider them the most robust estimates.

Reinvestment Rate	Time Horizon (years)	Bias (N = 3)	Bias (N = 6)	Bias (N = 9)	Bias (N = 12)
20.7%	3.0	4.3%	1.3%	0.7%	0.2%
Mid	3.0	4.6%	2.0%	1.3%	0.8%
30.4%	3.0	5.8%	2.9%	1.9%	1.4%
20.7%	4.3	6.8%	4.7%	3.7%	3.4%
Mid	4.3	6.7%	3.8%	2.8%	2.5%
30.4%	4.3	5.5%	2.7%	1.4%	1.3%
20.7%	7.5	9.3%	7.2%	7.0%	6.4%
Mid	7.5	8.3%	5.4%	4.5%	4.2%
30.4%	7.5	4.4%	2.3%	1.4%	1.1%

Table 2.3: IRR-MIRR Median Differentials for Simulated Funds (per annum)

This table presents the IRR bias for varying reinvestment rates and the number of invested deals (N). Bias is calculated as the difference between the average IRR of the typical private equity fund that makes N investments and distributes the proceeds to investors when the deals mature and the counterfactual case in which the proceeds are reinvested/discounted until the predetermined time horizon, using different reinvestment rates. The "Mid" reinvestment rate varies with N. As derived above, it includes $\frac{N-2}{2N}$ of the difference between the low (20.7%) and high (30.4%) rates.

Table 3 shows that our estimated biases are positive across this very wide range of assumed parameters for the number of projects per fund, the time horizon and the reinvestment rate.

The results also confirm that bias is smaller for funds containing more projects (higher N) as the QWA bias is reduced. Jenkinson, Kim and Weisbach (2021) report that the median buyout fund invests in nine projects. But, as discussed above, drawing nine projects at random from our historic dataset represents an unrealistic degree of diversification due to systematic risk and projects of unequal size. We correct this by setting N=6. This generates a realistic standard deviation of fund IRRs (Figure 3, below) whilst avoiding the need to specify the risk factors which account for this systematic risk. This assumption gives us our central estimate of 3.8% per annum bias: somewhat greater than the sum of our parametric estimates above for QWA bias (1.9%) and convexity bias (0.34%).

As a further robustness check, we repeat these MIRR calculations after removing any projects which recorded lives greater than 7.5 years. This only slightly reduces the central bias estimate (for N=6) to 3.5% per annum, confirming that this bias is not simply the result of a few exceptionally long-lived projects.

2.7 Stochastic Reinvestment

In this section, we compare the IRRs of conventional PE funds (which distribute the proceeds of mature projects to investors) with the returns generated if this cash is reinvested into new projects until a fixed horizon. We saw above that such a fixed-horizon return will be free from QWA and convexity biases, so the difference between the estimates derived based on these different assumptions will again give us an estimate of the size of these biases.

For robustness, we will derive estimates using two very different approaches and different datasets: (i) simulating reinvestment by each fund into new projects (in effect simulating the returns on "evergreen" funds); (ii) simulating the returns achieved by an investor who reinvests the cash distributed by a mature fund into a new PE fund. These approaches both remain fully invested over a fixed horizon and so will be free from QWA and convexity biases. [7]

2.7.1 Simulating PE Fund IRRs Using Project-Level Data

We first consider the returns generated by a PE fund which immediately reinvests the proceeds from each maturing project into a new project. These stochastic project returns could be modelled either parametrically or by bootstrapping historic PE returns. However, in either

[7]As a further robustness check, we tried shuffling the data to remove the covariance of project returns and maturities by matching each r_i with a randomly drawn T_i. However, this generates some projects which generate extremely large annual returns over a period of many years, resulting in massive dispersion of the final values generated by different projects. This resulted in correspondingly far greater volatility drag and diversification return than is seen in actual fund data. In removing the first-order QWA bias, this approach massively increased the second-order bias and thus did not generate useful results.

case, generating returns over a fixed investment horizon raises problems.

Consider an investment in an initial project which generates an annualised return r_1 and matures at T_1. These values are then fed into the IRR calculation, but to generate the corresponding annualised return up to our fixed horizon T^*, we need to simulate the return r_2 which is earned when this cash is reinvested. We know that r_2 is strongly correlated with the maturity T_2 of this second project, so if we select a project (either parametrically or directly from our historical dataset) with exactly the required maturity $T_2 = (T^* - T_1)$, the return on this project will be conditional on T_1, and hence on r_1. Thus simulating a return which exactly fits the horizon T^* threatens to produce very misleading results by generating autocorrelation of returns.

To avoid this, we must select reinvestment projects unconditionally. We draw these projects from the same pool as we used to select the initial projects with replacement. Once the final project extends beyond our pre-defined horizon, we discount its future liquidation value back to our horizon. Thus stochastic modelling still requires the use of an appropriate discount rate to generate our end-of-horizon valuations. Given this issue, taking a parametric approach to generating these reinvestment returns has little to recommend since it introduces the additional risk of a wrong parameterisation without avoiding the need for discounting.

Our simulations use the same project-level data as above. We simulate 10,000 funds with a life of 10 years. Each fund invests in private equity deals drawn from the project database with replacement. As discussed in section 4.1, we chose leverage parameters which generated net IRRs with a distribution in line with that observed empirically.

We assume that capital is called 2.5 years after being committed by investors (similar to the figure reported by Metrick and Yasuda (2010), although, of course, the IRR is calculated from the first cash flow rather than the commitment of capital). This leaves 7.5 years for the deals to be liquidated and the proceeds distributed back to the investors. Durations of the deals that exceed 7.5 years are capped at 7.5 years, keeping their IRRs fixed and recalculating their multiples accordingly (for robustness, in ongoing work, we model alternative assumptions).

The IRRs quoted by PE funds are calculated from the net-of-fees cash returned to investors, so to generate comparable data we also need to simulate these fees. There are four broad groups of fund fees for private equity funds: Management fees, transaction costs, carried interest and monitoring fees:

a) A typical buyout fund charges a management fee of 2% on the committed capital (during the investment period) and on the invested capital (during the harvesting period);

b) Each project is charged a transaction cost of 1% of the deal value (after 50% reimbursement to the investor, Metrick and Yasuda, 2010). For simplicity, we combine these with management fees as "Fixed Fees" in the tables below;

c) A carried interest of 20%, based on a hurdle rate of 8%, with catch-up, claw-back and a waterfall structure;[8]

d) Metrick and Yasuda (2010) report that monitoring fees are 0.40% of the firm value annually, but 80% of these fees are reimbursed to the investors. Since the remaining effect is negligible, we do not take these fees into consideration.

Our base case assumptions are a leverage ratio of 0.60 (defined as debt/assets), interest rate 7.5% and 2.5 years between the commitment of capital and the first call. As discussed above, we assume that each fund contains 6 independent projects since this makes allowance for an appropriate degree of systematic risk. Table 4 shows that our simulated fund fees are similar to those documented by Phalippou (2009). Figure 3 compares the Net IRR distribution of our simulated funds with the Net IRR distribution of the funds in the Preqin Cash Flow database. This shows that our base case assumptions produce a realistic distribution of net fund IRRs.

Panel A: Net IRR	Benchmark	Simulated	Difference
Mean	12.7%	12.7%	0.0%
Median	12.2%	12.5%	-0.3%
St. Dev	13.1%	13.5%	-0.3%
Panel B: Fees	Benchmark	Simulated	Difference
Fixed Fees	4.8%	5.3%	-0.6%
Performance Fees	2.0%	3.0%	-0.1%

Table 2.4: Actual and Simulated Fund Net IRRs and Manager Fees

This table compares the outputs of the PE fund simulations using the base assumptions (6 deals per fund, 60% leverage, 7.5% interest rate) with benchmarks. Panel A presents the comparison of Net IRR to the distribution of the actual fund IRRs in the Preqin Cash Flow database. Panel B compares the simulated fees to the ones documented by Phalippou (2009).

We will compare these simulated IRRs with the simulated returns of PE funds which reinvest the proceeds of their initial deals into new projects drawn with replacement from the same pool of PE projects until the end of our fixed horizon (10 years) so that the fund remains fully invested throughout this period.

For robustness, we introduce different levels of return persistence in the deals in which funds invest. Such persistence might be due to manager skill, or differences in the risk premia earned

[8] According to this structure, as long as the combined fund returns do not exceed a pre-defined hurdle rate (almost always 8%), all fund profit goes to the fund investors (limited partners). If the fund return exceeds the hurdle rate, the catch-up provision kicks in, and fund managers retain the excess profits until the total profits are shared as 80/20 between investors and fund managers. For further excess profits, an 80/20 split is maintained. Generally, the profit split is done on a deal level, and a claw-back provision results in a final rebalancing at the end of the fund life based on the total fund returns.

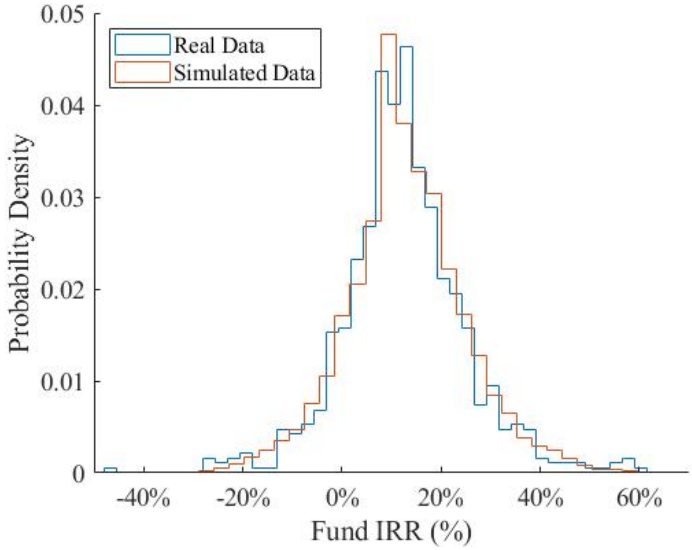

Figure 2.3: Simulated vs. Actual Fund Net IRRs (%)

This figure compares the Net IRR distribution of the simulation using the base assumptions (6 deals per fund, 60% leverage, 7.5% interest rate) to the distribution of the funds included in the Preqin Cash Flow database.

by funds specialising in different sectors or within sub-periods of our dataset. Performance persistence should be expected to reduce bias by reducing the cross-sectional variance of the returns on the projects in which funds invest. Our first reinvestment model (Model 1) assumes no performance persistence: successive deals are independent. Model 2 introduces a high level of performance persistence by drawing the reinvestment deals from the initial set of invested deals. Thus a fund which initially invested in successful deals is likely to continue to do so. Model 3 generates moderate performance persistence by drawing projects for reinvestment from one of two deal clusters. The first cluster includes all the deals drawn by the successful half of the PE funds, the second cluster includes the deals drawn by the other half of the PE funds. Both clusters include all deals, but the successful cluster has a higher share of the better ones.

We quantify the resulting persistence using a simple regression model of the annualised return of reinvestment deal k invested by fund f against the return on the fund's preceding deal $DealGMReturn_{f,k} = \beta DealGMReturn_{f,k-1} + \epsilon$. Model 1 generates β=0, Model 2 β=0.21, Model 3 β=0.13. By comparison, Braun, Jenkinson and Stoff (2017) look at the performance of successive projects by a given manager and find a regression coefficient of 0.102.[9] Thus, our different models introduce unrealistically little persistence (Model 1), unrealistically strong persistence (Model 2), and a more plausible central scenario (Model 3).

For each of these models we simulate the net IRRs of PE funds containing (i) nine projects

[9] Braun, Jenkinson and Stoff (2017) regress the PMEs of successive fund deals, whereas we use deal GM returns (IRRs), but as long as the market return (which is netted off the fund return when the PME is calculated) is assumed to have near-zero autocorrelation, the regression coefficients will be comparable to ours.

per fund (the observed median for buyout funds), and (ii) six projects per fund (which, as discussed above, generates a more realistic level of variance in our simulated IRRs).

We saw above that QWA and convexity biases are both due to variations in the maturities of the individual project returns within the fund (and hence in the timing of the cashflows returned to investors). We thus estimate the sum of these two biases as the difference between (a) the fund IRR without reinvestment (subject to both biases) and (b) with reinvestment over a fixed horizon (which removes both biases).

The results are shown in Table 5. As expected, a larger number of projects per fund results in lower bias, but despite this - and other differences between the models - the resulting bias estimates are in the relatively narrow range of 3.2% to 4.4%. Biases of this magnitude will clearly be highly economically significant to investors since they account for a significant proportion of the average net IRR of 12.2%.

These estimates are all slightly higher than the parametric estimates in Sections 4 and 5 (1.9% QWA plus 0.34% convexity bias). This can be attributed to the fact that these simulations: (i) avoid the simplifying assumptions required in our derivations and (ii) allow possible higher-order effects in addition to the first-order (QWA) and second-order (convexity). The fact that our simulations model net-of-fees fund IRRs and our earlier parametric estimates were based on gross project returns makes little difference since the assumed leverage in the latter was calibrated to match the empirically-observed volatility in net fund IRRs.

	N = 6			N = 9		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Median IRR (no reinvestment)	12.3%	12.3%	12.3%	12.4%	12.4%	12.4%
Median IRR (with reinvestment)	7.9%	8.9%	8.2%	8.9%	9.3%	8.9%
Median Bias	4.4%	3.4%	4.1%	3.5%	3.2%	3.5%
Performance Persistence	None	High	Mid	None	High	Mid

Table 2.5: Simulated Median Net Fund Returns and Implied Bias

This table compares the IRRs of the PE funds simulated using the base assumptions (60% leverage, 7.5% interest rate) for 6 and 9 deals per fund separately to the IRRs of the counterfactual funds, which reinvest the investment proceeds to new projects until the end of the fund life which is fixed to year 10. The comparison is made for three separate models, which differ in terms of the level of performance persistence during the reinvestments. In Model 1, the reinvestment project is drawn randomly independent from the past draws. In Model 2, funds reinvest by drawing from their initial set of N investments. In Model 3, funds draw from one of the two deal clusters based on their initial investments.

It is also worth emphasizing that Table 5 reports the median bias for each scenario (our earlier parametric estimates were, by their nature, means). The mean simulated biases are substantially higher, but we are again keen to be conservative in our estimates. For robustness, we also repeated these simulations whilst excluding all deals recorded after 2014 (in order to avoid any risk of self-selection resulting from deals which were not yet complete being omitted from the MergerMarket dataset). This left our central bias estimate unchanged at 3.4%.

Table 6 shows the corresponding bias estimates for different deciles of the IRR distribution, with substantial bias in all deciles.[10] We would expect this sorting to reduce the variance of project returns and maturities within each decile. The fact that this results in only a slight reduction in the overall median (from 3.4% to 3.0%) is a reassuring sign that our earlier estimates were not badly affected by the pooling of potentially heterogeneous projects (e.g. projects from different vintages, or from sectors with persistently different risk premia).

	Max. IRR	2	3	4	5	6	7	8	9	Min. IRR
Bias	2.9%	2.3%	2.0%	1.4%	1.9%	2.3%	3.3%	3.9%	5.7%	5.7%

Table 2.6: Median Simulated Bias by IRR Decile

This table presents the Median IRR bias separately for performance deciles.

2.7.2 Simulated Investor Recommitment Strategy

In this section, we simulate an investor who invests in a PE fund and subsequently reinvests the cash distributions from this fund into a new PE fund. This is another way of modelling the return which is generated by maintaining exposure to PE over a fixed time horizon and hence will be free of convexity and QWA biases. This alternative approach allows us to check the robustness of our earlier simulations using different assumptions and an entirely separate database.

We use the Preqin database of fund cashflows. This contains the data on 4,355 PE funds (with vintages between 1980 and 2018), including the dates and amounts of the cash inflows to the PE funds (capital calls) and cash distributions to the investors (net of fund manager fees). From the 30 different fund strategies included in the database, we limit our attention to buyout funds (consistent with our project-level simulations, which were calibrated to match the empirical distribution of net BO fund IRRs). We also filter out all funds with a vintage later than 2005 since these might still make significant future cash distributions (the typical private equity fund has a life of 10-13 years).[11] Consistent with other studies, we also filter out a small number of funds with extreme IRRs and very short durations, leaving a sample of 369 buyout

[10]For this decomposition to be meaningful we need to apply the high persistence assumption (otherwise unluckily low IRRs record higher fixed-horizon returns as reinvestments tend to be less unlucky – this is simple mean reversion rather than an indication of bias). With high persistence, reinvestment will on average be equally lucky as the initial project choices, although with some variation depending on the frequency with which the best projects among the initial projects are picked again for reinvestments.

[11]Kaplan and Schoar (2005), Phalippou and Gottschalg (2009) similarly eliminate funds younger than 10 years. We are more stringent in removing live funds since we require fund cashflows for our simulations. For this reason, we wish to remove live funds, which include a final valuation generated by the fund managers. For this reason, we eliminate funds younger than 13 years, considering the possibility of 3-year fund life extension.

funds.

Table 7 summarizes the main characteristics of this data. The mean (Median) IRR of PE funds is 12.2% (8.6%), in line with the summary statistics in Gupta, Nieuwerburgh (2019). The average fund calls 86% of its fund size (measured by committed capital) and distributes close to double the called capital, but with substantial variation - the worst-performing funds end up close to complete failure. On a value-weighted basis, these funds manage funds for an average of five years.

Metrics	Mean	Median	Min	Max
IRR	12.7%	12.2%	-46.8%	102.3%
Contributions (% of Commitments)	85.0%	86.0%	35.8%	146.3%
Distributions (% of Commitments)	163.0%	152.1%	4.5%	1171.8%
Duration (years)	5.0	4.9	1.3	10.7
Vintage	1998.9	1999	1980	2005

Table 2.7: Characteristics of Net Fund Cashflows (Buyout Funds)

This table presents the characteristics of the fund cash flow data. Fund IRRs are displayed in the first row. The second and third rows present the total amount of cash invested into and distributed out of the private equity funds as a percentage of the total capital committed at the beginning of the fund life. Duration is calculated as the average number of years the capital is distributed back to the investors, weighted by the present value of the amount distributed. Vintage is the year the private equity fund started its operations.

The investor commits to a PE fund, remits capital to the fund when it is called and receives distributions when the projects are exited. After the final cash flow, the fund IRR is calculated using the complete set of net cash flows. In the counterfactual scenario, distributions received by the investor are committed to another PE fund. Such "recommitment" strategies are widely discussed in the practitioner literature (e.g. Cardie et al., 2000, de Zwart et al., 2012, Nevins et al., 2004, Oberli, 2015). Endowment funds are known to reinvest in this way since they have allocations to PE which are not only substantial but also very stable over time (Azlen and Zermati, 2017). More generally, such reinvestment is generally implicit in investors' strategic asset allocation decisions, which typically assume that the chosen asset allocations are maintained throughout the investment horizon.

In practice, investors commit to multiple funds simultaneously in order to diversify returns and make their aggregate cashflows more predictable. We consider an investor who commits to a single fund and, when this fund has distributed sufficient cash, reinvests in another single fund. This is a less attractive strategy, but it generates returns which are a like-for-like comparison with the IRRs reported by individual funds. By contrast, a portfolio of such funds would generate additional diversification return which would interfere with this comparison.

Fund cashflows can extend considerably further than the maturities recorded for individual projects, so in order to allow investment in a sequence of funds (and also protect our estimates from excess sensitivity to projects which mature after the end of the investment horizon) we make this horizon substantially longer (40 years) than for our project-level simulations. At the end of this horizon, the investor stops reinvesting, and then all remaining distributions are collected and the resulting cash flows are used to calculate the annualised IRR. This leaves only slight residual variation in the effective horizon (all cashflows are received between 40 and 45 years), so the scope for QWA or convexity bias is very small. The difference between this figure and the average PE fund IRR gives us an estimate of the systematic biases. Unlike the project cashflows above, the Preqin dataset records the cash distributions from each fund net of fund manager fees, so no additional fee calculation is necessary.

For these two strategies to be comparable, we keep the investor's average cash holding close to zero, even though the cash calls by funds and cash distributions from funds are unpredictable. This assumes that investors sometimes borrow (or sell other non-private assets from elsewhere in their portfolios) in order to provide the cash called by a fund. Still, this assumption is required since positive net cash holdings would dilute investor returns, leaving us comparing the IRR generated on a fund fully exposed to PE with the return on a reinvested strategy with significant cash holdings or net borrowing.

Investors are assumed to collect distributions from their most recent fund for t years before making commitments to a new fund. At this point, they commit a multiple of the cash they hold into a new fund. The value of this multiple (a=1.55) is chosen to give an average net cash holding close to zero across these simulations. By the time this cash is called, funds are likely to have received further distributions from their previous investment. For robustness, we use different techniques for dealing with the short-term fluctuations in cash held by the investor. Our first method calculates the IRR over the full investment horizon, including cash distributions and cash calls as positive/negative cashflows. This IRR might in principle be biased, but any such biases are likely to be small because the strategy remains on average fully invested in PE over this long (and exogenous) horizon. By contrast, the IRRs published by funds will be affected by the very large variance (and covariance) of the project lives shown in Figure 1 above. Over 50,000 simulations, our reinvested investor IRR averaged 11.4%, compared to the average published IRR of 13.5%, suggesting a bias of just over 2.1%.[12]

As an alternative (and to avoid using an IRR), we instead assumed that cash balances were subject to a borrowing/lending rate of 10% until the end of the horizon. This generated a long-term investor return (in effect a MIRR) which also averaged 11% and so again suggested a bias of 2%. Assuming zero interest resulted in lower long-term investor return and hence a higher

[12]For VC funds, the bias is larger at around 4%, consistent with the greater variance of VC fund returns.

bias estimate. These simulations remain preliminary since we are investigating alternative simulation techniques which might be less granular and hence generate smaller absolute cash balances. However, whilst some simulated paths generated positive cash balances, others were negative (implying borrowing). With the average cash holding across our simulations close to zero, there should be little net effect due to simple gearing differences.

Thus, although still preliminary, these results are broadly consistent with the bias estimates we derived in earlier sections. This is reassuring since we are using a different method and an entirely separate database of net fund cashflows. Furthermore, we know that these latest estimates are likely to be conservative since they compare the IRRs of single funds against a reinvested strategy which is slightly better diversified (accumulated cash is reinvested into a single new fund, but the existence of residual cashflows from earlier funds will give an element of additional diversification). This will add further "diversification return" to the returns of the reinvested strategy and hence will reduce our estimated bias.

These estimates can be regarded as giving equal weight to all funds in our dataset since our simulated investors make the required commitment to each new fund regardless of the size of this fund. For robustness, we repeated this analysis using just the cashflows of the largest 50% of funds (thus removing the smaller funds that would arguably have been most overweighted). This generated marginally larger bias estimates.

Phalippou and Gottschalg (2008) note that the IRRs recorded by individual funds are sometimes aggregated together into an average for the PE sector as a whole, but this average will be a misleading indicator of the returns investors can expect to achieve since funds which record higher IRRs tend to be achieved be of relatively short duration. To correct for this (and the different sizes of funds), they weight fund IRRs by the PV of cash invested and the fund's duration, resulting in "a sort of IRR per year and per dollar invested", which is 2.42% per annum lower than the simple average of the fund IRRs. This differential is related to QWA bias to the extent that it is the covariance of the project returns and durations which leads to the observed covariance of fund IRRs and durations, although the latter could also result from sectoral, vintage or compositional differences within the dataset. However, QWA bias is distinct since it is not just a matter of aggregation - each individual fund IRR should be regarded as having potentially been boosted by QWA bias. Furthermore, duration-weighting the fund IRRs simplifies each fund into a single cash flow returned after the calculated duration, thus removing some of the effects of the covariance of individual project returns and maturities within individual funds. It also removes the convexity effect identified above. These factors help explain why this differential is lower than our bias estimates.

We have now estimated QWA and convexity bias both parametrically and by simulation, including simulations based on two entirely separate databases and using a wide range of different assumptions. This is grounds for confidence that the biases that we have identified are robust and economically highly significant.

2.8 Alternative Return Measures - Biases in Other Measures of Annualized Returns

Having established that the IRR is systematically biased, we now investigate alternative measures that have been suggested for measuring PE returns. This gives a useful additional perspective on the underlying factors causing QWA bias.

The PME (Public Multiple Equivalent) derived by Kaplan and Schoar (2005) is widely used in academic studies but seldom calculated by funds. It is defined as the ratio of two present values, using a time-varying discount rate which reflects the return achieved each period in a benchmark asset, typically the total return on an equity index such as the S&P500. A PME greater than one thus represents fund outperformance of this benchmark:

$$PME = \frac{PV(\text{total cash returned to investors})}{PV(\text{total cash invested})} \tag{33}$$

The cash multiple (Multiple of Invested Capital, MOIC) can be seen as a special case of the PME where the discount rate is set to zero. This measure is widely cited by funds, although it cannot be directly compared to the annualized returns recorded for other asset classes. To investigate the properties of the PME, it is useful to make the same simplifying assumption that we did for the IRR in section 3: that all the investor cash (K_0) is called by the fund at time t=0. All cashflows returned to investors in subsequent periods are discounted back to t=0 using the time-varying discount rate M_t:

$$PME = \frac{1}{K_0}\Sigma_{t=1}^{T}\frac{d_t}{(1+M_1)...(1+M_t)} \tag{34}$$

Substituting for d_t, using the identity $d_t = K_{t-1}(1+r_t) - K_t$:

$$PME = \frac{1}{K_0}\Sigma_{t=1}^{T}\frac{K_{t-1}(1+r_t) - K_t}{(1+M_1)...(1+M_t)} \tag{35}$$

$$PME = \frac{1+r_1}{1+M_1} - \frac{K_1}{K_0(1+M_1)} + \frac{K_1(1+r_2)}{K_0(1+M_1)(1+M_2)} - \frac{K_2}{K_0(1+M_1)(1+M_2)} + \frac{K_2(1+r_3)}{K_0(1+M_1)(1+M_2)(1+M_3)}... -$$

$$\frac{K_{T-1}}{K_0(1+M_1)...(1+M_{T-1})} + \frac{K_{T-1}(1+r_T)}{K_0(1+M_1)...(1+M_T)} - \frac{K_T}{K_0(1+M_1)...(1+M_T)} \tag{36}$$

We can ignore the last term since the investment horizon T will be extended until all assets have been written off or distributed to investors, so $K_T = 0$.

$$PME = 1 + \frac{r_1 - M_1}{1+M_1} + \frac{K_1(r_2 - M_2)}{K_0(1+M_1)(1+M_2)} + \frac{K_2(r_3 - M_3)}{K_0(1+M_1)(1+M_2)(1+M_3)} ... + \frac{K_{T-1}(r_T - M_T)}{K_0(1+M_1)...(1+M_T)} \tag{37}$$

The PME is thus a weighted average of the excess returns (in excess of the benchmark return M_t) recorded by the fund in each period. Recall the corresponding equation for the IRR:

$$IRR = \Sigma_{t=1}^{T} \frac{r_t K_{t-1}}{(1+IRR)^{t-1}} / \Sigma_{t=1}^{T} \frac{K_{t-1}}{(1+IRR)^{t-1}} \tag{38}$$

The PME and IRR can both be regarded as weighted averages of the periodic returns rt. In each case, the weight given to each periodic return is a function of the present value of the fund at the start of each period. However, the weights for the PME are functions of variables which are all simultaneous or prior to the periodic return in question, so these weights will not subsequently be revised as successive terms are added. By contrast, we can see that the IRR gives weights to each r_t which depend on asset values in all periods including those subsequent to the return in question (equation 3). This leads to a retrospective adjustment of these weights and hence QWA bias. Thus the IRR exhibits QWA bias, but the PME does not. The same is true for the cash multiple, where M_t=0 for all t.[13]

However, the weights on the excess returns in equation (37) sum to much greater than unity. This reflects that the PME is a multiple, not an annualized return. By contrast, for a meaningful measure of annualized returns, these weights must sum to unity since a performance measure with $\Sigma w_t \neq 1$ would be a biased estimator of the expected excess return (assuming that returns are drawn from a stable distribution). But setting $\Sigma w_t = 1$ introduces QWA bias because it means that earlier w_t must be adjusted retrospectively as subsequent periodic returns and distributions are added into the calculation.

The weights given to later returns r_t must be a function of the cash distributions that have been made over periods 1 to t-1. Otherwise, a substantial weight would be given to periodic returns even after the fund has already returned most of its assets to investors, leaving little

[13] In theory, a fund manager might be able to bias the MOIC: for example, if the first project in which the fund invested very rapidly generated an exceptionally large multiple, then the fund manager will know that subsequent investments are likely to dilute this exceptional multiple with more average values. Hence the fund's overall multiple could be boosted by abandoning any further investments and winding the fund up prematurely. However, this seems unlikely in practice since the amount of cash committed to the fund by LPs is fixed in advance. Failure to invest this full amount is likely to disappoint the LPs and would, of course, dramatically reduce the fees earned by the fund manager. Thus it seems unlikely that fund managers would choose to exploit this bias. This comes in dramatic contrast to the QWA bias analysed in this paper, which does not depend on discretionary fund manager action but is instead driven by the negative correlation between fund returns and duration shown in Figure 1, which appears to be a fundamental characteristic of the PE sector.

value in the portfolio. To be meaningful, an annualised performance measure must possess two properties: that wt should be a function of prior d_t, and that $\Sigma w_t = 1$. However, together these conditions imply that the weight given to early-period returns must also be a function of subsequent distributions. This retrospective adjustment will give rise to QWA bias if distributions are correlated with earlier returns, just as we saw above for the IRR.[14]

This has a very important implication: there is no point in looking for alternative functions which, like the IRR, seek to measure annualized fund returns using only the fund's periodic cashflows. Any such return would require weights w_t, which are adjusted to reflect cash calls and distributions and, coupled with the requirement $\Sigma w_t = 1$, this requires retrospective adjustment of earlier weights. This leads to an important conclusion: that QWA bias does not arise from the particular functional form of the IRR. Instead, it follows directly from the properties that we would demand of any meaningful measure of annualized returns.

Consistent with this, it is straightforward to show that the various alternative measures of annualized returns that have been suggested within the PE industry all suffer from QWA bias. These have been suggested as means of generating IRRs that compare fund cashflows with those on listed equities, giving a measure of the annualized outperformance by the fund. Confusingly, the first of these alternative measures is also referred to as the public market equivalent (PME), but it is generally attributed to Long and Nickels, so we will refer to it here as PMELN. PMELN compares the IRR of the fund cashflows with the IRR that would have been recorded for a similarly-timed set of investments in listed equities. The value of each cash call made by the fund is assumed to evolve in line with the total return on an equity index such as S&P500. Subsequent cash distributions by the fund are treated as the sale of these equities, leaving a reduced asset value invested in the equity index. These cashflows plus the residual asset value at the end of the investment horizon are then used to calculate a benchmark IRR. The difference between the fund's conventional IRR and this benchmark IRR is taken as a measure of fund outperformance.

One known problem with this approach is that the cash distributions of a fund which significantly outperforms the equity index may generate a negative residual asset value, implying that the fund is then being benchmarked against a short position in the equity index. This problem has been addressed by introducing a scaling factor for the implied equity flows (e.g.

[14] As discussed earlier, reliable periodic valuations of PE projects are not available until the project matures and is realised as cash or listed equity. We can infer the average periodic return r_i on this project between initial investment and maturity, but we have no reliable means of measuring how this return might have varied over time (r_{it}). Nevertheless, the cross-sectional correlation shown in Figure 1 between the maturity of individual projects and their average return will itself translate into a time series correlation between r_t and d_t for the fund in aggregate. High-return projects tend to mature quickly, and after they mature, the average return on the fund's remaining projects will fall. Thus substantial returns of cash to investors on average tend to be followed by lower subsequent aggregate fund returns, leading to a positive QWA bias.

the Capital Dynamics PME+ measure and the Cambridge Associates mPME).

A more fundamental question is whether these measures suffer from QWA bias. They each compare the fund IRR with the IRR of equivalently-timed investments in public equity. We know that the fund IRR suffers significant bias as a result of the correlation between project returns and project maturities. Only if the second component (the IRR of the public equity equivalent) is equally biased will these two biases net off, leaving the overall measure unbiased.

This requires that the covariance between the returns and durations of the projects within the fund must be entirely due to systematic risk rather than idiosyncratic risk. This seems extremely unlikely since (i) annualized returns on PE projects show far greater volatility than publicly-listed equity (annualised standard deviation of returns on the S&P500 has been around 12% compared to the (maturity-weighted) standard deviation of project annualised returns of 64% in our dataset); (ii) estimates of the market beta for fund returns have been around unity (see section 2). Hence the majority of the volatility in project returns is idiosyncratic. It remains theoretically possible that the observed covariance of PE project returns with their maturities comes about because maturities covary massively with the market return but are independent of idiosyncratic risk. To assess this, we can regress the average duration of funds within each vintage against subsequent equity index returns. Figure 4 shows that there is some systematic effect of strong market returns on durations, but this is far smaller than would be required to generate the observed covariance of project returns and durations without any effect from idiosyncratic returns (to generate the observed 64% standard deviation of returns, the regression coefficient would need to be greater than 5).

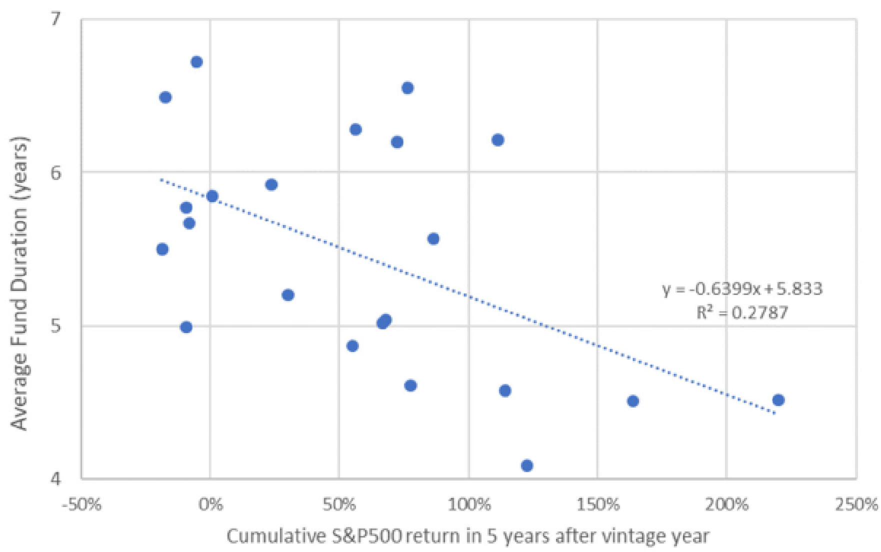

Figure 2.4: Average Fund Duration by Vintage Year vs. Subsequent Equity Returns

Direct Alpha is another performance metric used by practitioners. This is calculated by deflating each of the cashflows into and out of the fund by the cumulative return on the equity index up to that point. The IRR of these deflated cashflows is then calculated and is interpreted as representing the annualized excess return generated by the fund. This figure will suffer from QWA bias for exactly the same reasons as PMELN since the deflated project returns are likely to show a strong negative covariance with T_i. The fact that these alternative measures all suffer from QWA bias demonstrates that the sources of this bias have not previously been well understood.

2.9 Conclusion

The IRR has long been known to be sensitive to the impact of early cash returns. However, the reasons for this have not previously been fully analyzed. We identify two systematic upward biases in the IRRs quoted by PE funds. These arise because the timing of the cash distributions made by funds to investors (i) is stochastic (resulting in convexity bias), and (ii) covaries with the returns achieved up to this date ("Quit Whilst Ahead" bias). By contrast, the returns on more liquid assets are calculated over exogenously fixed horizons, and so are free from these biases. Thus the IRRs quoted by PE funds are upwardly-biased compared with the returns on other asset classes such as listed equity, with which they are likely to be compared. Survey evidence clearly shows that investors continue to regard fund IRRs as a key factor when deciding to make commitments to funds.

We quantify the biases in PE IRRs using a range of parametric and simulation techniques. These show robust upward bias that raises a typical fund IRRs by an average of around 3% per annum (it could be far higher in individual cases). This is economically highly significant to investors, compared to the average net fund IRR of 12.2% per annum. We have shown that these biases are not just the result of a small number of extreme data points. To this end, our estimates are deliberately conservative in a number of respects. Consistent with other studies we removed extreme returns and durations from our dataset of PE projects. We also reported the median biases in our simulations (the means are substantially higher, implying that individual fund IRRs can in some cases be substantially higher). We considered alternative scenarios which (i) removed projects with the longest lives; (ii) modelled the performance of individual deciles of the IRR distribution (consistent with persistent differentials in manager skill levels or the risk premia involved); (iii) checked our project-based simulations against an entirely separate dataset of net fund cashflows by modelling an investor reinvesting in successive funds.

QWA bias does not arise from the particular functional form of the IRR, it follows directly from the properties that we would demand of any meaningful measure of annualized returns. Variants on the IRR have been suggested by practitioners (Direct Alpha, ICM/PME, PME+, mPME). We have shown that these are similarly biased. The fact that practitioners have proposed such biased measures demonstrates that the biases in the IRR have not previously been properly understood. We demonstrated that cash multiples and Public Multiple Equivalent (PME) are not biased, but they would become biased if they were annualised.

Neither IRRs nor related measures should be relied upon. Unbiased performance measures instead need to be calculated over fixed time horizons. PE funds should publish their performance on this basis. In practice this would be best achieved by calculating some form of MIRR (modified IRR). There is inevitably scope for debate about the returns assumed to be achieved by reinvesting early cash distributions, but any standardized calculation method would remove the potentially very large biases that are inherent in private equity IRRs.

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Chapter 3

Fair Value Measurement and Private Equity Fund Interim Valuations

Abstract

Private equity investors require accurate estimates of the market value of their investments to perform optimal fund allocations and correctly diversify their portfolios. Since private equity investments are mostly privately held and do not have an active market valuation, these estimates rely on the subjective valuations of the fund managers. Previous research documents inaccurate valuations that lag behind the real intrinsic values of the investments. This paper shows that adopting fair value accounting increases the accuracy of the interim fund valuations of buyout funds significantly. This increase is not temporary, is accompanied by the increased valuation effort of the private equity funds and is robust to the possible confounding effects of the global financial crisis. Beneficial effects of local fair value measurement standards spill over to the funds in other geographies, mainly due to the peer pressure effect. Fair value measurement eliminates the significant heterogeneity in valuation quality stemming from the difference in fund investor profiles.

3.1 Introduction

During the last decade, private equity fund interim valuations have been the subject of criticism by market participants and a main point of interest for academic research. The focus of the discussions has been the level of accuracy of these interim period valuations, i.e. the difference between fund valuations and fair values of the fund investments. Since private equity funds generally invest in private companies without active market valuations, fair values of investments can only be observed following the sales of these investments by the fund. Therefore throughout the fund life, private equity investors rely on the valuations of the fund managers to assess their performance.

This study focuses on evaluating the effects of the “ASC 820 - Fair Value Measurements” accounting standard on the accuracy of private equity fund valuations. This standard was introduced in 2008 to increase the informativeness of the financial statements and promote better comparability among the statements of different firms, by demanding a large subsection of assets and liabilities to be marked to market. Although fair value measurement and accounting standards that promote it has a long history before ASC 820, it is the first standard that directly affects the private equity industry since it explicitly requests the “illiquid investments” to be fairly valued, using the methodologies detailed in the standard. Private equity fund managers, who dominantly kept their investments at historical cost or used the valuation of the latest round of financing, questioned the proposed changes because of their difficulty of application to the private equity industry, and the possibility of increased volatility in fund valuations (Kreutzer, 2009).

Evaluating the effects of fair value measurement on private equity fund valuation accuracy is essential due to several reasons. First, there is a significant information asymmetry between the private equity fund managers and investors. The investors have no say in fund investment decisions, no prior information about the time their committed capital will be called by the fund managers, and no direct access to the portfolio companies invested. Throughout the fund life of 10 years (or more) during which they usually are locked up in their investments, their knowledge on the performance of their investments depends on the limited amount of information provided by the fund managers. If this information is inaccurate or outdated, highly-sophisticated private equity investors end up with no sources of reliable data to perform investment decisions correctly. Using this data, they may end up with wrong decisions about (i) optimal portfolio allocations and diversification (ii) investment in the follow-on fund of the same fund family. According to PricewaterhouseCoopers (2008), investors consider reporting quality and fund performance of equal importance when they evaluate the continuation of their business relationship with a fund firm. An improvement in the information quality due to the introduction of fair value measurement would alleviate, at least partially, the information asymmetry among the parties, contributing to the investment decisions of investors.

Second, the private equity secondary market has been significantly growing during the last decade, especially after the financial crisis, fueled by the need for urgent liquidity of private equity investors. In this over-the-counter market, bids are made as a percentage of the most updated Net Asset Values ("NAV") of the fund. Deepening of the private equity secondary market would alleviate the illiquidity issues identified with the private equity industry, and the reliability of the fund NAVs is crucial for this market to be well-functioning and efficient. Therefore, an improvement in fund valuation accuracy resulting from the introduction of fair value measurement would make a significant contribution to the industry by increasing the efficiency of the secondary market.

The analysis of this paper is based on a slight modification of the framework laid out by Jenkinson, Sousa, and Stucke (2013), in which they exploit the relationship between fund distributions and quarterly valuation updates to draw inferences regarding the accuracy of the interim fund valuations. This framework relies on a simple mathematical relationship which shows that: (i) When a fund values its investments correctly, at the time of a sale of an investment and the accompanying distribution to the investors, the book value will exactly match the sales price. Therefore there will be no valuation update (ii) When the fund values its investments inaccurately, which can be because of an estimation error or the lack of effort to perform valuation, at the time of the distribution, the difference between the sales price and book value of the investment will be automatically inputted as a fund valuation update. As the accuracy of fund valuations decreases, the relationship between distributions and quarterly valuation updates deepens. So the relationship between fund distributions and quarterly valuation updates can be utilized to assess the accuracy of the fund valuations.

The first part of the empirical analysis shows that the accuracy of the buyout fund interim valuations significantly increases after the introduction of ASC 820. Before the standard, the book value of the average buyout investment at the time of its sale is 50% of its sales price, whereas this figure jumps to 86% following ASC 820, showing an economically and statistically significant convergence towards the fair values of investments.

Increased fund valuation accuracy is not enough to conclude that there is a permanent improvement that can be attributed to the introduction of ASC 820 since the valuation accuracy is also directly affected by the market conditions. For example, let us consider an asset with a market value of 150 but the book value is 100, either because of an estimation error or lack of effort to update its valuation. These values suggest a valuation inaccuracy of 50. If the asset prices in the market start to decrease, pushing the market value of the asset down to 120, even if the fund manager exerted no valuation effort and the book value is still 100, meaning that there is no effect that can be attributed to the valuation practices, valuation inaccuracy decreases from 50 to 20. This example also shows us that under low valuation effort, changes in market conditions strongly affect the valuation accuracy. So one needs to make sure that (i) the improvement in valuation accuracy is not a temporary result depending on market-related factors but it is persistent (ii) the change is accompanied by increased valuation effort of the fund managers.

To evaluate the arguments of the previous paragraph, I begin by showing that the valuation accuracy is persistently higher for all years after the introduction of ASC 820, with a significant decrease in its volatility. I also argue that the increase in fund valuation accuracy is accompanied by increased efforts to update valuations according to the developments in the market. To support this argument, I first show that the correlation between the valuation inaccuracy and market returns, which was 0.78 before the ASC 820, completely disappears after the introduction of the standard. This finding is important because, as shown in the example presented in the previous paragraph, in the absence of valuation effort, the relationship between market returns and valuation accuracy intensifies. The fact that their correlation significantly decreased after the ASC 820 constitute substantial support for the argument that fund effort increased after the standard.

In the next step, I present that the effects of the interaction of distributions with market returns on fund valuation updates significantly decrease after the introduction of the standard. Under a low valuation effort, a higher combined effect of market conditions and distributions on the valuation updates would mean that a distribution that occurs when prices are increasing (decreasing) would result in a larger (smaller) valuation update, for book values lower than market prices. A significant decrease in the coefficient of the interaction term after the introduction of the standard tells us that the changes in market prices at the time of the distribution result in a smaller effect on valuation updates since the fund exerts effort to take the developments in the market into account before the distribution happens.

The second part of the empirical analysis investigates the global effects of ASC 820. I show that although ASC 820 is a local accounting standard that targets private equity funds located in the US, the valuation principles it introduced are implemented by the European funds in a similar way. I discuss that “Peer Pressure” is one of the underlying factors of the global spill-over of the effects of this local accounting standard. Since all private equity funds try to receive investments from the same pool of institutional investors, even the local European fund firms without any operations in the US significantly improve their valuation quality after ASC 820 to sustain competitiveness.

Finally, in the last part of the paper, I evaluate the effects of investor power on valuation accuracy. Within a propensity score matching framework, I show that before ASC 820, investments from large private pensions result in higher valuation accuracy. However, after ASC 820, this difference diminishes, pointing to a significant increase in standardization in the private equity industry in terms of valuation practices.

This study relies on the fund cash flow data obtained from Preqin. The final sample of this paper includes quarterly valuation data for 981 buyout funds located either in Europe or in the US. Observations in the final sample span the period from 1985 to 2018. The database also includes other information such as fund name, fund firm vintage year, geography and industry focus. Using this database, I form an unbalanced panel consisting of around 25,000 quarterly fund valuation observations. For additional analyses, the database is supplemented by additional information received from Eikon and Bloomberg Professional terminals.

This study contributes to several strands of literature. Various other papers investigate the effects of ASC 820 on fund valuation accuracy, and they end up with conflicting results. These papers rely on variations of a similar method in which future cash flows from a private equity fund/investment are discounted using a discount factor to calculate an NPV for each quarter, and quarterly NAVs are compared to this NPV to calculate the valuation inaccuracy. The main drawback of these methods is that they rely on perfect foresight, i.e. there is an inherent assumption that funds should be able to estimate all future cash flows at any given time. This assumption is problematic because of two main reasons: (i) PE funds invest committed capital during the long investment period (generally the first half of the total fund life), with irregular intervals. NPV methodology assumes that funds have the capacity to perfectly estimate the future value of investments that are not even made yet. (ii) Given the existence of the global financial crisis that coincides with the introduction of ASC 820, this methodology inevitably punishes the valuation observations before the standard since the valuation effects of the financial crisis are impossible to foresee from years before. To overcome these issues, I build my methodology based on isolated quarterly observations. This method evaluates individual quarter observations without reliance on future cash flows and helps us to distinguish any valuation inaccuracy from prediction inability. I find a significant increase in valuation accuracy for buyout funds, as in Crain and Law (2017). I also provide evidence that funds exert more effort to value their investments accurately and provide significant support for the hypothesis that the improvement in reporting accuracy can be attributed to the introduction of ASC 820 and not any other market-related factors, such as the global financial crisis. This paper also contributes to "peer pressure" and "institutional ownership" literature since it is, in my knowledge, the first paper to discuss peer pressure effects on private equity valuations and the causal effects of having powerful investors on board on valuation accuracy, by taking advantage of differences-in-differences and propensity score matching methodologies.

The paper proceeds as follows: Section 2 lays out the background related to private equity valuations. Section 3 discusses the related literature. Section 4 introduces the related regulatory framework and ASC 820 standard. Section 5 defines the empirical methodology. Section 6 describes the data used in the empirical analysis. Section 7 presents the results. Section 8 concludes.

3.2 Private Equity Funds and Interim Fund Valuations

A private equity fund is a partnership of fund investors, called the limited partners ("LP"), and the fund managers, called the general partners ("GP"). The LPs of a typical private equity fund are generally highly sophisticated institutional investors that have the aim of achieving a well-diversified portfolio. The GPs are private equity firms with significant expertise in acquisitions, value creation, and exits. For this partnership, the LPs commit the capital necessary for the investments to be made, and GPs manage this capital to provide satisfactory returns to the investors.

Private equity funds are closed-end funds with a typical life of 10 years, which may be extended for a few years with the consent of the LPs, depending on the limited partnership agreement ("LPA") that formalizes the relationship between the GPs and the LPs. During the fund's first few years (typically five), the focus of the GPs is to locate suitable investment opportunities and perform investments. For each investment to be made, the GP asks from the LPs a portion of the committed capital to be released and injected into the fund. So although the LPs know how much capital they allocate to a specific fund, they do not exactly know when this capital will be called. During the second half of the fund life, the GPs are mostly concentrated on successfully exiting from the investments and distributing the proceeds to the investors, net-off the fund fees.

In a typical private equity fund, the fund investors are not involved in the daily operation of the fund, and they have no say over the investment decisions of the GPs. Private equity fund managers report the fund investment performance to the fund investors every quarter. Although not required by any regulation (Cumming and Walz, 2010), quarterly performance reporting to investors is an industry standard for the private equity industry mainly because of 2 reasons: (i) Information-hungry, sophisticated private equity investors have no other means to learn how have their investment been performing during the fund life of 10 years. Therefore they demand regular performance reporting and generally require it to be expressed clearly in the LPA (ii) US and Europe Private Equity Associations support and encourage quarterly disclosure to limit the information asymmetry among the GPs and LPs. For example "Invest Europe" (previously "European Venture Capital Association"), which is a non-profit organization which defines itself as the "guardian of the industry's professional standards, demanding accountability, good governance and transparency from our members.", promotes quarterly reporting to investors in its regular "Investor Reporting Guidelines" (Invest Europe, 2018).

Since the majority of the investments made by the private equity funds are to private companies that are not listed on a stock exchange and have no active market valuation, the performance metrics presented to the investors rely on the valuations of the GPs about their investments. The Carlyle Group LP (2013) acknowledges the subjective nature of these valuations fact with the following words:

"Valuation methodologies for certain assets in our funds can involve subjective judgments, and the fair value of assets established pursuant to such methodologies may be incorrect, which could result in the misstatement of fund performance"

Interim fund valuations are essential for fund investors due to several reasons. First, private equity investments have been considered to be highly beneficial by sophisticated investors since by having returns that have a low correlation with the market returns, they contribute to the risk-return balance of their portfolio. According to Preqin (2019), close to 60% of private equity investors consider the diversification benefits to be the main reason for investing in private equity. However, Welch and Stubben (2018) argue that the main reason for this low correlation with the market returns is the fund valuations that are infrequently and inadequately updated by the fund managers and the failure of these valuations to reflect the real economic value of the fund investments.

Second, since there is asymmetric information between the GPs and LPs, the LPs seek signals that would inform them about the expected future performance of the private equity fund to be invested in. Since well-established private equity firms prefer to roll out a new fund every 3-5 years, there is generally another fund of the same fund firm which is already in operation and performing investments. So the LPs that are looking for a home for their capital use the reported performance of the current fund of the fund firm as a signal for the expected future performance of the fund that they are considering investing in. Nevertheless, since there is no active market valuation for the private investments of the current fund, the performance evaluation of the LP relies exclusively on the subjective interim valuations of the GPs.

Third, the transaction prices in the secondary markets for private equity investments significantly rely on the NAVs of the funds. As explained by Albuquerque et al. (2018), the secondary market intermediaries receive bids for the private equity funds as a percentage of the current reported NAVs, and the discount on the bid is mainly motivated by the search for a liquidity premium of the buyer.

3.3 Literature Review

Recent research approaches interim fund valuations from different angles and mostly ends up with conflicting results. Jenkinson, Sousa, and Stucke (2013) compare quarterly distributions with NAVs and find that overall, private equity fund valuations are significantly conservative. The study finds that, on average, the investments held by private equity funds are undervalued by around 35%. The main reason for this significant undervaluation is reported to be the tendency of fund managers to stick to valuation based on historical costs with a risk-averse approach. Also, Brown, Gredil, and Kaplan (2019) show that top-performing funds likely understate their valuations. On the other hand, Jenkinson et al. (2020) compare the difference between quarterly NAVs and discounted future cash flows of buyout funds using a fixed (11%) discount rate and find that although there are significant time-series differences, on average, buyout fund valuations do not display a significant systematic bias. Compared to the design of this paper, my methodology is free from the potential adverse effects of an arbitrary discount rate assumption. Plus, it does not rely on future fund cash flows since although this approach might be relevant for the valuation of various other asset classes, it does not fit the structure of the private equity funds. Full deployment of the committed capital for PE funds into investments takes years, and this complex cash flow structure is not compatible with the assumption that fund managers need to have perfect foresight regarding the future values of even the investments that are not done yet.

Several recent studies evaluate the contribution of ASC 820 to the valuation accuracy of private equity funds, ending up with different conclusions. Brown, Gredil and Kaplan (2019) evaluate fund returns and return autocorrelations before and after the adoption of ASC 820 and do not find a significant improvement in buyout fund valuation accuracy. As the paper discusses, this method is not able to distinguish between the effects of the financial crisis and the introduction of ASC 820. Jenkinson et al. (2020) comment that improvements in valuation accuracy start earlier than the introduction of ASC 820.

Easton, Larocque, and Stevens (2018) compare reported NAVs with the present value of the future cash flows, discounted by fund IRRs as Jenkinson et al. (2020). They find no improvement in NAV Bias (which is defined as the difference between NAV and NPV) for buyout funds after the implementation of ASC 820. In addition to the discussion on the suitability of using DCFs in the PE context, this paper has two additional methodological properties that differ from my approach: Firstly, the paper uses final fund IRRs as discount rates. This approach expects funds to perfectly estimate the future performance of their investments from day 0 and treats the high and low performers significantly differently. Plus, funds with negative IRRs are expected to immediately decrease their NAVs after performing an investment. Secondly, the evaluation of the benefits of ASC 820 requires the comparison of valuation accuracy for two sub-periods, before and after November 2008. Nevertheless, given that investments made before ASC 820 lived through two financial crises (the Dot.Com crisis and the Credit Crunch), DCF comparison of NAVs significantly punishes the investments exited during these periods. On the contrary, the period after ASC 820 is relatively calm, with markets generally moving upwards without significant volatility, which increases the forward-looking capability of the PE funds.

Crain and Law (2017) estimate a stochastic discount factor using the approach introduced by Korteweg and Nagel (2016) to calculate the NPV of the future cash flows of each investment and compare the NPV with the reported NAVs. They report significantly increased valuation accuracy after the implementation of ASC 820. This paper is different from others in that it assesses the valuation accuracy at the portfolio company level instead of the fund level. Although using investment-level valuations lets better precision in valuations, it is not informative on the overall accuracy of fund valuations. Plus, like Easton, Larocque, and Stevens (2018), the comparison of DCFs with quarterly NAVs potentially conflates valuation accuracy with prediction ability, which is determined by the market conditions and structurally differs for different periods.

Valuation practices of the private equity firms during the fundraising for their next fund have also attracted significant attention from academics. Several papers focus on evaluating the possible motivation of the funds to inflate their fund valuations during the fundraising for their next fund, to attract investors by misinforming them about their quality. Jenkinson, Sousa, and Stucke (2013) report that there is significant value inflation during fundraising, which is gradually corrected afterwards. Barber and Yasuda (2017) find that low-reputation GPs inflate fund NAVs before the fundraising of the follow-on fund. Similarly, Brown, Gredil and Kaplan (2019) show that some underperforming managers inflate reported returns when fundraising takes place. Conversely, Huther (2018) argues that the increased valuation at the time of the fundraising is because of the successful investments with earlier exits, and there is no systematic value inflation on a deal level.

This paper is also related to the literature on peer pressure effects and institutional ownership on voluntary disclosures. Lin, Mao and Wang (2018) show that an increase in institutional ownership and the resultant improvement in the information environment of the top Russell 2000 index firms create pressures on their industry peers to increase voluntary disclosures. Using a similar empirical approach, Boone and White (2015) find that higher institutional ownership is associated with greater management disclosure. My paper contributes to this literature by providing first-time evidence that peer pressure and investor power affect the disclosure quality in the private equity industry.

3.4 Reporting Regulations and ASC 820 Standard

3.4.1 Reporting Requirements for Private Equity Funds

Financial reporting standards for public firms are governed by International Accounting Standards Board ("IASB") in Europe and Financial Accounting Standards Board ("FASB") in the United States. Both of these institutions are independent, private-sector organizations that date back to the early 1970s that are founded to sustain consistent financial reporting practices that facilitate comparability among different firms. IASB and FASB regulate the financial reporting of public firms by their "Accounting Standards", which are periodically updated. US firms prepare periodic financial statements in accordance with the "US Generally Accepted Accounting Principles" ("US GAAP") of FASB. Europe firms are expected to comply with the "International Financial Reporting Standards" ("IFRS") of IASB. Although these two sets of standards diverge in some detailed approaches, overall, they have the same aim of making sure that public companies produce reliable and comparable financial statements. Also, IASB and FASB have been working together to eliminate different practices and produce a single set of reporting standards in the future.

Although the technical details regarding the quality of financial reports are governed by the independent accounting authorities introduced above, the overall health of the public markets is kept under control by the Security Commissions of each country, such as "Securities Exchange Commission" ("SEC") in the US and "Financial Conduct Authority" ("FCA") in the UK. These institutions have the shared responsibility of protecting investors and sustaining orderly transactions in the markets. Security Commissions rules necessitate public firms to produce and issue quarterly financial reports in accordance with the local accounting standards.

For private firms, reporting requirements differ for different countries. In the US, private firms are not bound by the SEC rules regarding quarterly financial reporting. Although private investment firms are further regulated by the "Investment Companies Act of 1940", which requires the investment companies to comply with SEC requirements, private equity funds mostly benefit from exemption since most of these funds have less than 100 investors. Private firms are also free to decide whether to comply with US GAAP rules. FASB states that "compliance with GAAP standards for many for-profit private companies is a choice, rather than a requirement because private companies can often control who receives the financial information" (Financial Accounting Standards Board (FASB), 2006a).

In Europe, however, private firms face somewhat stricter reporting regulations. Based on the Fourth Council Directive (European Union (EU), 1978), private firms that operate in European Union countries are strictly required to issue a defined set of financial statements, including balance sheets and income statements, on an annual basis.

In accordance with the discussion above, being a private investment company, private equity funds are either not legally obliged to report financial statements or bound with light requirements to report on an annual basis. As the industry grew and became more complicated, the lack of transparency due to the limited regulations was addressed by the Industry Associations through their non-binding valuation and reporting guidelines. European Associations led by the British Venture Capital Association ("BVCA") and European Venture Capital Association ("EVCA") tried to lead the private equity industry towards high-quality reporting by the International Private Equity and Venture Capital Valuation Guidelines ("IPEV). In the US, Private Equity Industry Guidelines Group ("PEIGG") was formed with the same intention. These associations have issued valuation guidelines since the 1990s and have tried to initiate regular and high-quality reporting in the private equity industry. These guidelines have been regularly updated in accordance with the revisions in the financial reporting standards introduced above.

Although the regulations regarding the reporting of private equity funds are not strict, quarterly reporting of funds to their investors in accordance with the accounting standards is a dominant industry practice. The most important reason for this is the demands of LPs, which are large and sophisticated institutional investors, for periodic updates regarding their investments. This requirement is also supported by the valuation and reporting guidelines introduced above. It becomes a signal of low quality if a fund does not comply with this industry standard. The funds are also bound by the requirements of their institutional investors regarding compliance with the GAAP. The LPs, such as pension funds, tend to include a clause in the partnership agreement requiring the GPs to comply with the local GAAP (Easton, Larocque, and Stevens, 2018).

3.4.2 History of Fair Value Measurement and ASC 820

As Emerson, Karim and Rutledge (2010) highlight, criticisms of the historical cost accounting date back to 1962, the “Accounting Research Study No:3” of the Accounting Research Division of American Institute of Certified Public Accountants (“AICPA”). This study proposed the changes in asset values that can be objectively determined to be recognized in accounting books. However, the first real steps towards fair value accounting were taken in 1993, with the introduction of SFAS 115 by FASB. As Jones (1988) puts it, “historical costs no longer faithfully represented the economic realities of today’s complex instruments”, leading the FASB to take a step towards “fair value approach” in valuations. SFAS 115 was followed by several updates during the decade, each incrementally increasing the level of complexity of the valuation methods and the number of asset and liability types to be measured based on fair value.

Although previous statements contributed to the fair value concept, they failed to eliminate the confusion regarding the definitions and valuation methodologies used. As of September 2006, FASB released the “Statement on Financial Accounting Standards No. 157, Fair Value Measurements” (“SFAS 157”). By releasing this statement, the FASB aimed to address the problems caused by different definitions of Fair Value and reporting inconsistencies resulting from these dispersed definitions. As a result of the update in FASB Accounting Standards Codification as of September 2009, the name of SFAS 157 was updated as “ASC 820”.

ASC 820 standard defines fair value as “the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date". This definition especially highlights its focus on "the price received to sell the asset" (exit price) instead of "the price that would be paid to acquire the asset" (entry price) since entities do not necessarily sell the assets at the prices paid to acquire them. (Financial Accounting Standards Board (FASB), 2006b)

The distinctive property of ASC 820 that is of particular interest to the private equity industry is that, on top of all the requirements of previous statements, it requires illiquid investments that have no market valuations to be measured based on the fair value measurement standard. Since this definition applies to almost all investments of a typical private equity fund, these funds become obliged to apply fair value measurement for their investments. To clarify the methods to be applied while performing the fair valuation of assets, ASC 820 introduces the "Fair Value Hierarchy", which specifies three levels of information that will be used as inputs to valuations. Level 1 inputs are the quoted prices in active markets for identical assets. Therefore ASC 820 gives the highest priority to Level 1 inputs for fair value measurement. Level 2 inputs are the observable information other than the quoted market prices for identical assets. These inputs may be quoted prices for similar but not identical assets, quotes for identical assets in inactive markets, or other observable information that is useful for the valuation of the asset. Level 3 inputs are the unobservable information that may be used as inputs to asset valuation. ASC 820 demands these inputs to "reflect the reporting entity's expectations about the assumptions that market participants would use in pricing the asset". Since private equity investments are mostly private firms not traded in active markets, fair valuations of private equity investments in the ASC 820 context rely mostly on Level 2 and Level 3 inputs.

FASB required ASC 820 to be valid from fiscal years beginning after November 15, 2007. The statement gave the firms the right to delay the application of the statement for one year until fiscal years beginning after November 15, 2008. Europe and US Private Equity and Venture Capital Associations supported the standard by updating their valuation guidelines accordingly.

In Europe, the first significant move towards fair value was with "IAS 39 - Financial Instruments" of IASB, which was issued even before the ASC 820 in 2004. IAS 39 had the same purpose of sustaining fair value measurement, but its effect on private equity was limited since it explicitly stated: "If the range of reasonable fair value measurements is significant and the probabilities of the various estimates cannot be reasonably assessed, an entity is precluded from measuring the instrument at fair value." The European equivalent of ASC 820, "IFRS 13 - Fair Value Measurement" standard was issued only in 2011, to be effective from January 2013.

3.5 Methodology

Net Asset Value of a private equity fund is the current value of the capital invested by fund investors. Therefore they are calculated by excluding any debt obligations and possible fees to be earned by the fund managers on the unrealized investments. Fund NAV is updated by the fund managers and reported to the investors quarterly, with additional details regarding fund investments and other performance metrics.

Three activities build up the total change in the NAV of a private equity fund in a given quarter. First, the fund locates suitable investment opportunities and invests in them. To do this, the fund calls capital from the investor, creating a capital injection into the fund. Second, the fund exits from some of its investments and deducts the book values of these investments from the NAV, and third, the fund updates the valuations of its existing investments. So we can formulate the change in NAV of fund i in quarter q as follows:

$$\Delta NAV_{q,i} = CapCall_{q,i} \text{ - } BookVal_{q,i} + \Delta VALUPD_{q,i} \tag{1}$$

In the equation above, $\Delta NAV_{q,i}$ represents the net change in the total Net Asset Value of the fund, $CapCall_{q,i}$ is the capital injection into the fund from the investors, $BookVal_{q,i}$ is the total book value of the investments exited during the quarter which is deducted from the fund NAV, and $\Delta VALUPD_{q,i}$ is the valuation updates of the invested capital, regarding the existing investments for fund i in quarter q. The book value of the exited investments can be rephrased as follows:

$$BookVal_{q,i} = Dist_{q,i} \text{ - } \Delta VALERR_{q,i} \tag{2}$$

In Equation (2), "Dist" represents the proceeds from exited investments received during quarter q, and $\Delta VALERR_{q,i}$ is the difference between sales proceeds and the book value of these investments, in other words, the valuation inaccuracy. This equation shows that the relationship between Dist and $\Delta VALERR_{q,i}$ would tell us how close the book values are to the market values. For a book value that is lower(higher) than the sales proceeds, we can observe that a higher distribution results in a higher(lower) valuation inaccuracy. If, on the contrary, Book Values are regularly and successfully updated, we would observe much smaller valuation inaccuracy after a distribution. So the level of $\Delta VALERR_{q,i}$ that we observe after a distribution is informative on how accurate the fund valuations are. Unfortunately, the variables $BookVal_{q,i}$ and $\Delta VALERR_{q,i}$ are not observable. Replacing BookVal in Equation (1):

$$\Delta NAV_{q,i} = CapCall_{q,i} \text{ - } Dist_{q,i} + (\Delta VALUPD_{q,i} + \Delta VALERR_{q,i}) \tag{3}$$

In Equation (3) the variables $\Delta NAV_{q,i}$, $CapCall_{q,i}$ and $Dist_{q,i}$ are observable and available. This gives us the opportunity to calculate the sum of the two remaining variables, written in the parenthesis. Rephrasing ($\Delta VALUPD_{q,i}$+ $\Delta VALERR_{q,i}$) as $\Delta VAL_{q,i}$:

$$\Delta NAV_{q,i} = CapCall_{q,i} \text{ - } Dist_{q,i} + \Delta VAL_{q,i} \tag{4}$$

Equation (4) is a restated version of Equation (1) that breaks down $\Delta NAV_{q,i}$ to observable variables. $\Delta VAL_{q,i}$ represents the total valuation updates for fund i in quarter q, combining the valuation errors uncovered after a distribution, and the valuation updates on existing investments. Using Equation (2), we have already discussed the relationship between quarterly distributions and valuation inaccuracy. Since the variable that represents the inaccuracy ($\Delta VALERR_{q,i}$) is a component of $\Delta VAL_{q,i}$, Dist will be related to $\Delta VAL_{q,i}$ and this relationship can be exploited to make inference on the valuation accuracy. We can clarify the discussion above by using a simple example based on two hypothetical funds with valuation accuracy at two extremes. For simplicity, I will assume that there are no fund fees and leverage. The first fund is able to value its investments correctly at any given time. Therefore, a given investment which has a value of 100 in the accounting books of this fund will indeed be sold for 100. In this case, at the time of the sale, the NAV will decrease by 100, the distributions will go up by 100, and there will be no other effect on $\Delta VAL_{q,i}$, as a valuation update.

For the second case, we can introduce a fund with inaccurate valuations. For the same asset that is sold for 100, let us assume that this fund had a valuation of 60 in the accounting books. As the sale transaction is realized, the NAV of the fund will decrease by 60, the distributions will increase by 100, and the difference of these amounts will be mechanically inputted in the data as a valuation update of existing investments, $\Delta VAL_{q,i}$. To summarize, when the valuation accuracy increases, the effect of a distribution on fund valuation updates decreases, and vice versa. So, under the assumption that $\Delta VALUPD_{q,i}$is conditionally independent of Dist, meaning that all possible confounding variables that are both related to these two variables are controlled for, the effect of Dist on $\Delta VAL_{q,i}$ will tell us the degree of valuation inaccuracy for that fund.

How can we make sure that we have conditional independence between distributions and valuation updates of existing investments? Figure 1 helps us to discuss this question. As discussed, $\Delta VAL_{q,i}$ is the total valuation update for a fund during a given quarter. This is a variable that can be observed. It has two components, $VALUPD_{q,i}$ and $VALERR_{q,i}$, and these variables have a 1-to-1 effect on $\Delta VAL_{q,i}$. These two variables are not observable. We are interested in the relationship between Dist and $VALERR_{q,i}$, but since $VALERR_{q,i}$ has a

1-to-1 relationship with $\Delta VAL_{q,i}$ this is equivalent to observing the relationship between Dist and $\Delta VAL_{q,i}$. The problem is, the other component of $\Delta VAL_{q,i}$, $VALUPD_{q,i}$ is possibly confounded with Dist, i.e. there are some variables that co-affect the quarterly distributions and valuation updates.

The first group of these confounding factors are the market-related ones that affect each fund in a similar way. For example, a decrease in market liquidity may result in a decrease in distributions since sales opportunities will be limited. It may also result in decreased valuations because of a possible simultaneous decline in market prices. To control for these kinds of market-related effects, we need to take into account a variable that will control for the changes in market conditions. A suitable one is the changes in S&P 500 index, as it is frequently used in the literature with the same purpose.

Another systematic factor may be the "fourth quarter" effect introduced by Jenkinson, Sousa and Stucke (2013). Q4 is the financial audit period, and as a result of the comments from the auditors, valuations of existing investments are updated with higher frequency and amount during Q4s. At the same time, one can argue that the amount of distributions may structurally differ from other quarters due to the end of the calendar year. Therefore we need to control for the Q4 effect in our analysis.

The second group, investment-specific factors, is much more challenging since these variables are not observable. These are the variables that are specific to individual funds and investments, which have the potential to relate to both variables of interest. It would be helpful to discuss several causes which may potentially result in a bias in our findings. First, if the portfolio company that is sold in a specific quarter has experienced a significant incident during the same quarter that significantly affected its final sales price (For example, a new contract with a large customer that boosts future revenue prospects up), the relationship between Dist and $\Delta VAL_{q,i}$ variables will be much less informative on valuation errors. However, it would be fair to comment that the considered effect would be minimal since having a major value-changing incident and being sold during the same quarter can be considered a rare and random incident. Second, the funds may have a regular habit of updating the valuations of all of their existing investments, specifically when they perform a sale of one of their portfolio companies. If this is the case, the total valuation update of the fund in a given quarter will no longer be informative about the valuation inaccuracy of the capital invested in a specific investment which is sold during the quarter, creating an upward or downward bias in the coefficient of interest depending on the sign of the valuation update. However, again, the possibility of this kind of practice can be speculated to be small, and I have no information on such systematic industry practice. Still, a large battery of fixed effects as control variables (Fund, Fund Age, Observation Year) needs to be included in the empirical analysis to minimize the possible effects of these unobservable confounders.

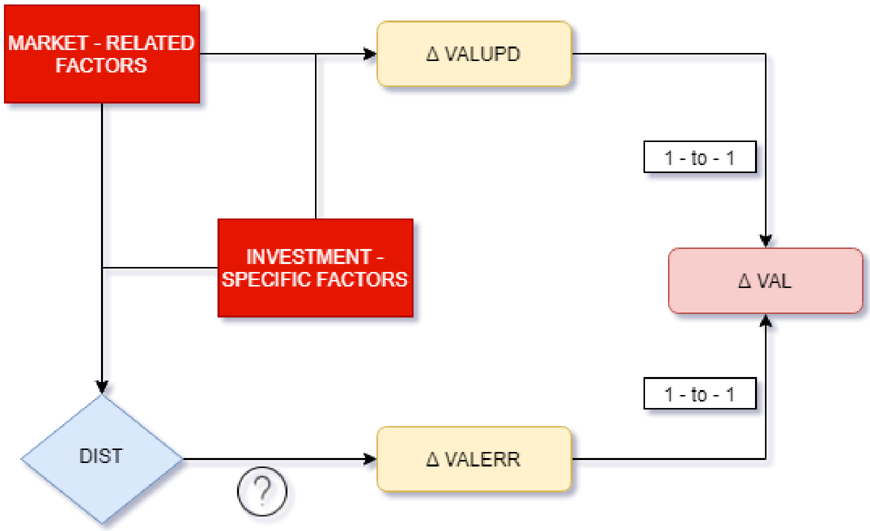

Figure 3.1: Relationship between Main Variables of Interest

This figure presents the relationship between the main variables of interest. "ΔVAL" is the total valuation update performed by a fund during a quarter. "ΔVAL" is the sum of "ΔVALUPD", voluntary valuation updates, and "ΔVALERR", valuation errors uncovered only after a divestment. "Dist" is the proceeds of a divestment distributed to the investors. Uncovering the level of valuation inaccuracy boils down to the evaluation of the relationship between Dist and ΔVAL, which is confounded by market-related and investment-specific factors which need to be accounted for, to capture the causal effect.

Based on the detailed discussion above, I base the empirical analysis of this paper on the relationship between the distributions and the fund valuation updates. The main test specification is:

$$\Delta VAL_{q,i} = \alpha + \beta_1\ CapCall_{q,i} + \beta_2 Dist_{q,i} + \beta_3 \Delta SP500_q + \beta_4 Q4_q + \gamma X_{q,i} + \epsilon_{q,i} \qquad (5)$$

The purpose of the specification in Equation (5) is to evaluate the relationship between the quarterly valuation updates and distributions, controlling for variables that have the potential to create a confounding effect and to identify a possible change in the degree of this relationship. For the majority of the analysis in this paper, an adjusted version of Equation (5) will be used to observe the changes in β_2, which represents the degree of valuation inaccuracy, after the introduction of ASC 820. $Dist_{q,i}$ is the distributions made to the investors following an investment sale by fund i at quarter q. $CapCall_{q,i}$ is the capital injections to fund i at quarter q by the investors, to perform an investment. ΔSP500$_q$ is the quarterly rate of change in the S&P 500 index. $Q4_q$ is an indicator variable that takes the value of 1 for quarter observations that belong to the 4th quarter of any year and 0 otherwise. Apart from these variables, all specifications control for fund, fund age and year fixed effects unless stated otherwise. These fixed effects are represented by matrix X in Equation (5). I follow the conservative approach regarding standard errors outlined in Cameron and Miller (2015) and report heteroskedasticity - robust standard errors that are clustered at the aggregate (fund firm) level, to eliminate the effects of a possible autocorrelation of residuals within the same fund firms.

This study relies on the fund cash flow database of Preqin, which is collected based partially on the voluntary reporting of the GPs. This fact has the potential to constitute a survivorship bias since low-performing or discontinued fund firms might have a lower incentive and tendency to share their cash flow data. If there is such a survivorship bias in the data, one could expect the coefficient of interest to have a downward bias, since these low-performing funds might be expected to have worse valuation practices and higher valuation inaccuracy compared to the others.

3.6 Data

This study is based on Preqin's "Private Equity Cash Flow Database". Preqin is one of the leading data providers for the private equity industry, and their data has been frequently used by academic research (e.g. Phalippou (2014), Ang et al. (2018)). Preqin has several sources of information to compile its database on private equity funds. They receive data directly from the GPs who volunteer to supply information. They also collect data from LPs based on the Freedom of Information Act ("FOIA"), which necessitates that public institutions share information regarding their activities when requested by members of the public. The third source of information is public filings. Brown et al. (2015) report that as of 2015, 58% of Preqin data is obtained from volunteering GPs, 39% is received from the LPs, and 3% comes from public filings.

The database includes three types of data items for each fund: "Capital Call", "Distribution" and "Value". Capital Calls are the requests of fund managers from the investors to inject a portion of the committed capital into the fund to perform an investment. Distributions are proceeds from an investment, net of any debt obligations and fund fees, delivered to the investors. The database includes daily capital call and distribution data for each fund. On top of the daily cash flow data, the database includes the "Value" items which are the quarterly net asset valuations for each fund performed by the fund managers. Quarterly "Value" transaction lines reported by the database also collect all the cash flow movements, capital calls and distributions, for the observation quarter. So simply, the database provides us with the $\Delta NAV_{q,i}$, $CapCall_{q,i}$ and $Dist_{q,i}$ variables of Equation (4) for fund i, quarter q. Using the provided data, I construct the last variable in Equation (4), $\Delta VAL_{q,i}$, the quarterly valuation updates for each fund and each quarter, which will be used as the dependent variable for the analysis.

As of August 2018, the database comprises 131,701 quarterly valuation observations from 4,355 private equity funds of 1,588 unique fund firms. These funds are of 30 different fund types, including buyout, venture capital, infrastructure and real estate funds. Apart from the cash flow and valuation data, the database includes fund and fund firm name, fund size, vintage year, fund stage as of the observation, and geography and industry focus information. Cash flow and valuation data are already standardized for all funds, based on a fund commitment of $10 million. I further normalize these variables by reporting them as percentages of fund size.

In the study, I limit the attention to buyout funds to eliminate any dilutive effects of pooling different fund categories together. The buyout fund category is the one with the longest history and largest transaction sizes. Its strategy of "acquiring, managing and selling mature firms" best suits the identification strategy applied in this paper, which aims to use sales proceeds to build inference on valuation accuracy. Venture capital funds, which are generally evaluated in the related literature, are also left out since these funds generally invest in very young firms that are extremely difficult to value, therefore it may be wrong to reach similar conclusions for these funds as it is done for buyout funds, based on the methodology applied in this paper.

Since my analysis relies on an advanced regulatory framework and structured accounting principles, geographically, I focus the attention solely on funds operating in the United States and Europe. As discussed in Section 4, governing bodies in Europe and the US have transformed the accounting framework to represent the value of the investments better. I filter out other geographic locations to eliminate possible biases resulting from the lack of high-quality accounting practices and valuation methodologies.

As mentioned in Section 2, a typical buyout fund has a lifetime of ten years, which can be extended for a few years with the approval of all investors, depending on the conditions mentioned in the LPA. To eliminate any possible effect of data errors, I filter out observations with fund ages above 10 years. For some of the analysis, I do robustness checks by extending the fund age to 13 years, in which I find no significant difference in the presented results.

Using the data filters mentioned above results in an unbalanced panel of 25,133 quarter observations from 981 buyout funds of 433 unique fund firms, spanning the years between 1985 and 2018. Table 1 presents the descriptive statistics of the final sample. The table is designed to report the data characteristics separately for each observation year. Periods 1985 - 2008 and 2009 - 2018 are reported in separate blocks since ASC 820 standard is introduced at the end of 2008. Columns 2 - 4 provide fund-level data. The second column breaks down the number of funds in terms of their vintage years. According to Bain & Company (2018), each year from 2005 to 2017, 200 to 300 new buyout funds were formed globally. For the same period, the final sample of this study includes 27 to 71 funds, with total coverage of around 25%. As expected, the number of buyout funds covered by the sample booms during the expansion period before and dramatically decreases after the global financial crisis.

The third column presents the total fund size for each year in million USD. Fund size represents the total investor commitments to the funds. The final sample captures a total fund size of $1.7 trillion. When compared to the yearly global buyout fund commitments presented by Bain & Company (2018) for the years 2003 to 2017, this represents a total commitment coverage of around 58%, ranging between 32% - 93% of global buyout fund commitments for each year.

In the fourth column of Table 1, we observe the average fund size for each year in million USD. Significantly higher fund size coverage (58%), compared to the fund count coverage (25%), suggests that the sample has a larger average fund size compared to the global buyout fund population, which is not surprising since fund firms with higher reputation and larger fund sizes are more inclined to share their data voluntarily. We observe a significant increase in average fund size from 2002 to 2008 and a significant drop with the crisis. The size of an average buyout is yet to reach the peak levels achieved in 2006. The two sub-periods have similar average fund sizes.

Column 5 of Table 1 presents the number of quarterly observations per year. In line with the increase in the number of funds, the number of observations also significantly and regularly increases over time. Since the number of funds is higher for the period between 2009 - 2018, the sample has a higher number of observations for that period.

Columns 6 to 8 inform us about the yearly evolution of the main variables of interest for this paper. These variables are presented after being standardized as a percentage of fund size. "ΔVAL" represents the quarterly valuation updates performed by the fund. On average, a typical buyout fund updates the valuation of its existing investments upwards by 1.9% of the fund size per quarter. This figure significantly decreases and turns to negative during the "Dot.com" crisis of 2001-2002 and "Credit Crunch" of 2008-2009. "Dist" is the quarterly distributions made by the fund managers to investors after exits from investments. Funds distribute 3.3% of the fund size on average per quarter. The distribution pattern follows the valuation updates, with significant slow-down during financial crises and dramatic increases during booms. "ΔSP500" is the change in S&P 500 index during the observation quarter. Column 8 presents the average quarterly change in S&P 500 index for each observation year. Average distributions and valuation adjustments are similar for the sub-periods, but the average change in S&P500 is much lower for the period between 1985 and 2008 because of the effect of the major financial crises experienced during this period.

Figure 2 lays out a non-parametric analysis of the relationship between distribution and valuation adjustments. This relationship constitutes the foundation of this paper by letting us build inferences on fund valuation accuracy. Panel (a) of Figure 2 uses columns 6 and 7 of Table 1 to let us observe the yearly changes in average distributions and valuation adjustments as a percentage of fund size. A strong relationship between distributions and valuation adjustments is evident, with significant decreases during financial crises and sharp increases afterwards. During crisis periods, funds exit from their investments much less frequently, either because of non-existent demand or because they do not want to sell at significantly decreased prices. The valuations of their existing investments are adjusted downwards during the same periods. When things turn to normal, sales increase and valuations are adjusted upwards.

Although Panel (a) of Figure 2 is helpful to see the yearly changes in distributions and valuation adjustments, it does not give us a clear picture of how the intensity of the relationship of these variables changes over time. In Panel (b), we observe how the correlation of these two variables evolves over time. Blue circles represent the correlation between these two variables for each year. Horizontal blue lines are the correlations for sub-sections 1985 - 2008 and 2008 - 2018. In this figure, we observe high correlations before 2008, with the exception of the crisis period of the early 2000s. Correlation is volatile, changing significantly from year to year, with a level of 0.5 for the whole sub-period. After 2008, however, we observe a completely different case. After the fall during the global financial crisis, the correlation remains low and consistently around 0.2, which is also the correlation for the 2008 - 2018 sub-period.

Year	#Funds	Total Size	Average Size	Quarter Obs	ΔVAL	Dist	ΔSP500
1985	3	1,402	467	1	-0.006	0.000	0.120
1986	2	59	29	14	0.037	0.004	0.039
1987	4	1,373	343	29	0.012	0.030	-0.010
1988	7	2,789	398	41	0.012	0.013	0.028
1989	2	267	133	63	0.008	0.012	0.061
1990	5	1,993	398	81	0.018	0.011	-0.012
1991	2	242	121	92	0.018	0.005	0.061
1992	8	1,127	140	109	0.012	0.012	0.013
1993	8	2,986	373	135	0.042	0.044	0.017
1994	13	6,372	490	164	0.020	0.024	-0.002
1995	13	9,109	700	200	0.031	0.059	0.076
1996	17	6,702	394	241	0.022	0.045	0.048
1997	22	23,396	1,063	274	0.053	0.045	0.072
1998	38	38,200	1,005	337	0.013	0.045	0.072
1999	30	33,547	1,118	408	0.041	0.043	0.051
2000	34	56,561	1,663	486	0.006	0.034	-0.030
2001	21	23,855	1,135	572	-0.016	0.020	-0.019
2002	24	23,705	987	642	-0.007	0.019	-0.049
2003	17	30,979	1,822	701	0.018	0.027	0.068
2004	26	33,396	1,284	800	0.032	0.049	0.025
2005	54	98,679	1,827	895	0.038	0.057	0.009
2006	69	213,269	3,090	1,066	0.030	0.046	0.034
2007	60	156,468	2,607	1,210	0.034	0.049	0.009
2008	57	151,668	2,660	1,374	-0.022	0.017	-0.113
Subtotal_{Pre}	536	918,151	-	9,935	-	-	-
Average_{Pre}	22	-	1,713	414	0.017	0.037	0.001
2009	27	37,774	1,399	1,445	0.009	0.008	0.061
2010	34	27,430	806	1,447	0.025	0.022	0.034
2011	40	84,688	2,117	1,492	0.016	0.028	0.005
2012	55	87,589	1,592	1,597	0.021	0.032	0.032
2013	51	64,035	1,255	1,694	0.023	0.033	0.068
2014	64	119,530	1,867	1,815	0.019	0.037	0.028
2015	61	97,784	1,603	1,831	0.020	0.040	-0.001
2016	71	158,545	2,233	1,798	0.022	0.035	0.023
2017	40	98,234	2,455	1,675	0.030	0.042	0.045
2018	2	1,071	535	404	0.028	0.032	-0.002
Subtotal_{Post}	445	776,685	-	15,098	-	-	-
Average_{Post}	45	-	1,745	1,520	0.021	0.031	0.031
Grand Total	981	1,694,837	-	25,133	-	-	-
Average	29	-	1,728	739	0.019	0.033	0.020

Table 3.1: Descriptive Statistics

This table presents the overall characteristics of the data used in the analysis. The data is detailed for each observation year, and it spans the period from 1985 to 2018. The second column breaks down the number of funds in terms of their vintage years. The third and fourth columns inform the reader regarding the total and average fund sizes for each year, in million USD. Column five reports the number of quarterly observations for each observation year. Columns 6 - 8 present the characteristics of the data regarding the main variables of interest. These columns present the average yearly valuation updates (ΔVAL), distributions (Dist) and changes in S&P 500 index (ΔSP500). The data in columns 6 - 8 are standardized by fund size. The table is presented in two blocks, separated for the sub-periods 1985 - 2008 and 2009 - 2018. Totals and averages are provided where relevant for the sub-periods and the full sample.

Panel (c) Moves one step further to enhance our understanding of the data and the change in the relationship between distributions and valuation adjustments after ASC 820. This figure distinguishes between the observations before and after ASC 820 standard and builds 100 clusters for each sub-samples based on the level of distributions. Each dot in Panel (c) represents one of these clusters. Blue markers represent the observations after ASC 820, and orange markers are for the ones before. The two trend lines help us to clearly see how the relationship between these two variables changes after 2008. Indeed, for both sub-periods, the observations are aligned around the trend lines, which show a significant decrease in the slope. After 2008, distributions are much less related to the valuation adjustments.

Of course, the relationships discussed in this section can never be adequate for us to reach conclusions on causality. There may be other confounding factors that would explain the co-movement of distributions and valuation adjustments, such as the changes in market conditions. The next section focuses on identifying the causal relationship between the two variables of interest by accounting for a wide range of possible confounders.

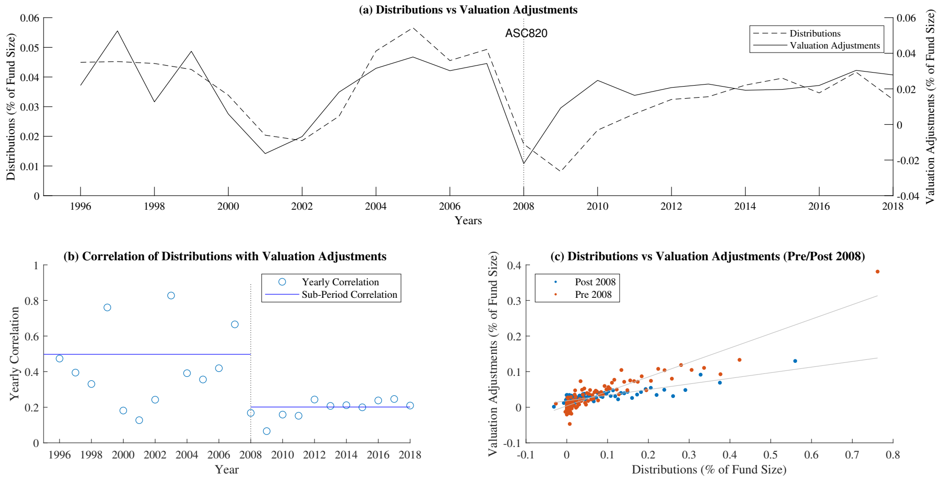

Figure 3.2: Distributions vs Valuation Adjustments

This figure presents non-parametric analyses regarding the main variables of interest. Plot (a) compares the yearly movement of distributions and valuation updates. Plot (b) presents the yearly correlation of distributions and valuation updates. Markers represent the yearly correlation coefficients, and horizontal blue lines highlight the correlations for both sub-periods. Plot (c) groups the observations to percentiles based on the distributions and evaluates the relationship between distributions and valuation updates for both sub-periods.

3.7 Empirical Results

3.7.1 Overall Accuracy of Fund Investment Valuations

The first step of the empirical analysis is to apply the methodology introduced in Section 5 to evaluate the overall accuracy of the buyout fund valuations in a very similar fashion to Jenkinson, Sousa, and Stucke (2013). My aim in this section is to reproduce their findings with my dataset to make sure that the starting point of this paper is in line with the previous literature.

Table 2 presents the results of the set of regressions based on Equation (5). The first column introduces capital calls and distributions as independent variables. In the second column, I include fund, year and fund age fixed effects. By adding these effects, I aim to control for possible confounding effects related to the distinct characteristics of specific funds, possible changes in fund behaviour related to the age of the fund (in quarters) as of the observation date, and the effects related to the observation year. In Column 3, I include the quarterly changes in S&P 500 index and the Q4 dummy variable that highlights the transactions in the last quarter of the year. By including the S&P 500 returns in the regression, I aim to capture the effect of market-related variations on the valuation updates. Q4 dummy helps to identify the effects of the "Audit Period" on the firm valuations. Column 4 of Table 2 addresses the possible concern that quarter observations without distributions may have diluting effects on the results by eliminating all observations with 0 distributions. In column 5, I ease the fund age limit of 10 years by keeping all observations during the first 13 years of the fund life to make sure that the age limit imposed on the database does not affect the results significantly. Finally, in Column 6, I filter out all observations of the years 2008 and 2009 to eliminate the potentially dilutive effects of the global financial crisis, which coincides with the introduction of ASC 820.

For all specifications, the "CapCall" coefficient is minimal and statistically insignificant. This is a natural result since the injections to the fund are expected to have a 1-to-1 effect on the NAV, but there is no reason for these injections to result in a valuation update of the existing investments.

The variable of interest, "Dist", has a high and consistent coefficient in all specifications, which is between 32.7% - 33.9% when year, fund and age fixed effects are accounted for, and the coefficient is statistically significant at 1% level for all specifications. The intuition of this figure is straightforward: On average, buyout funds' interim valuations are around 33% lower compared to the actual economic value created by their investments. This claim can be simplified by saying that the average buyout fund's book valuation of its average investment is two-thirds of the market value of this investment. This is a strong result, and its robustness to different model and data specifications significantly increases its reliability. This figure is almost perfectly in line with the findings of Jenkinson, Sousa, and Stucke (2013). It signals a significant conservatism in private equity investment valuations, which leads to low informativeness for the fund investors. Anecdotal evidence recently shared by Phalippou (2020) is in line with this result. Phalippou (2020) includes a response from Blackstone, one of the largest PE houses globally, to some claims made in the paper regarding fund performances. A sentence in this response (which is included in the paper) is as follows:

"The IRRs/MOICs you cite include a substantial number of unrealized investments. His-

torically, we've realized such investments at a 30 percent premium to their unrealized marks."

Overall, this finding constitutes strong support for the results presented by Welch and Stubben (2018), which suggest that the so-called diversification benefits of private equity investments are a result of inaccurate interim valuations.

Table 2 presents "ΔSP500" variable coefficients in columns 3-6. The coefficients that are positive and significant at 1% level suggest that the changes in market conditions, proxied here by the changes in S&P 500 index, affect the funds' valuations of their existing investments. However, the figures between 7.6% - 14.0% are a signal that this reflection is limited, and funds are tentative to use the market returns as an input that affects their valuations on a 1-to-1 basis. In column 6, the coefficient falls to 7.6%, which tells us that the chaotic environment during the financial crisis created a temporary sensitivity to market conditions. Eliminating those observations helps us to see the effect of market conditions on fund valuation updates during normal times. Overall, all specifications present a significant and robust relationship but also a tendency of fund managers to absorb or delay a significant portion of market effects without reflecting them in their valuations on a timely basis, which is consistent with the inferences made using the coefficient of the "Dist" variable.

The other variable in Table 2 is "Q4", a dummy variable that highlights the observations in the last quarter of any year spanned by the dataset. Since the fourth quarter of each year is the audit period, fund valuations are reassessed by an independent audit firm and revised according to their suggestions. The table presents positive coefficients that are significant at 1% for all specifications. The coefficients of 0.8% - 1.3% suggest a positive but small effect of independent audits on fund valuation updates. The figure and its statistical significance are maximized in Column 6, in which the observations during the crisis period are eliminated. Overall, the Q4 effect explains around 1% of the valuation updates.

The results reported in Table 2 highlight the conservative valuation approach of private equity fund managers, either as a result of the risk-averse approach that aims to beware any necessity to explain large swings in investment valuations to the fund investors by merely moderating the level of new information to be used or because of an effort-avoidance approach which relies on the perception that the only result that matters is the one when the investment is exited, therefore the effort exerted for interim valuations are unnecessary. The result of this conservative approach is the valuation increases in audit quarters, limited effect of market conditions on valuations, and immediate valuation spikes after distributions.

	(1)	(2)	(3)	(4)	(5)	(6)
CapCall	0.011	0.008	0.003	0.014	0.012	0.010
	(0.021)	(0.023)	(0.023)	(0.040)	(0.022)	(0.025)
Dist	0.383***	0.338***	0.338***	0.327***	0.335***	0.339***
	(0.041)	(0.044)	(0.044)	(0.043)	(0.040)	(0.047)
$\Delta SP500$			0.109***	0.140***	0.099***	0.076***
			(0.012)	(0.019)	(0.011)	(0.014)
Q4			0.009***	0.013***	0.008***	0.011***
			(0.002)	(0.003)	(0.002)	(0.002)
Year FE	NO	YES	YES	YES	YES	YES
Fund FE	NO	YES	YES	YES	YES	YES
Age FE	NO	YES	YES	YES	YES	YES
Observations	25,133	25,133	25,133	11,732	29,429	22,314
Adjusted R^2	0.146	0.164	0.170	0.292	0.173	0.173

Table 3.2: Overall Interim Valuation Inaccuracy

This table presents the results of panel regressions in which the dependent variable is the quarterly valuation updates of existing fund investments. All models include the quarterly capital calls (CapCall), and distributions (Dist) as independent variables. All quarterly cash flow data (valuation updates, capital calls and distributions) are normalized as a percentage of the fund size. Models 3 to 6 include quarterly changes in S&P 500 index (ΔSP500) and a dummy variable highlighting fourth-quarter observations (Q4) as independent variables. Models 2 to 6 include observation year, fund and fund age (measured in quarters) fixed effects. Models 1 to 3 rely on base data filtering in which fund age is restricted to 40 quarters (10 years), and observations with zero distributions are kept. Model 4 filters the database by eliminating all quarterly observations with zero distributions. Model 5 extends the fund age limit to 52 quarters (13 years). Model 6 eliminates all observations in the years 2008 and 2009 to prevent the possible confounding effects of the financial crisis. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the fund firm level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

3.7.2 Valuation Accuracy after ASC 820

The next step is to evaluate the effects of ASC 820 on the accuracy of the interim fund valuations, building on the methodology discussed and applied in the previous section. To do this, I revise the model introduced in Equation (5) to capture the change in the coefficients of the independent variables of interest after November 15, 2008, the date ASC 820 became fully effective. The results of the analysis are reported in Table 3, which presents the coefficient estimates for the observations before the introduction of ASC 820, and changes in these estimates after the introduction of the standard (coefficients including the term “x Post”). All specifications include observation year, fund age and fund fixed effects. I also control for the capital calls but do not publish them in the table since the results are statistically insignificant and have no relevance to the analysis. In column 1, I introduce the quarterly distributions as the independent variable. In column 3, I include the variables for quarterly S&P 500 returns and the Q4 dummy. In the fifth column, I address the possible concern that very old observations may have inflating effects on the coefficients received for the observations before the introduction of ASC 820 since the valuation practices may be expected to have lower quality compared to more recent periods. For this purpose, I eliminate all observations before the year 2000. I also take into account the fact that the timing of the global financial crisis perfectly coincides with the introduction of the ASC 820 standard and may have diluting effects on the results obtained through the analysis. To address this possible issue, I apply the same method as Easton, Larocque and

Stevens (2018) and eliminate all observations in 2008 and 2009 in columns 2,4 and 6, which use the same model specifications as their previous columns.

The coefficient of the "Dist" variable tells us about the buyout funds' valuation inaccuracy before the introduction of ASC 820, and the coefficient estimates are around 0.5 for specifications 1 to 4. All estimates are statistically significant at 1% level, and they tell us that during the period before the introduction of the ASC 820 standard, the book value of the average investment of an average buyout fund is half of its real economic value. When the observations before 2000 are eliminated, the figure stays around 43-44%, which is economically highly significant.

The second coefficient estimate in Table 3, "Dist x Post", informs us about the change in the valuation accuracy after the introduction of ASC 820. Given the high and positive estimate for the period before ASC 820, A negative (positive) estimate would mean that valuation accuracy increases (decreases) after the standard. All specifications presented in Table 3 highlight a negative coefficient, consistent and robust to different model and data specifications, and statistically significant at 1% level. Considering the first two coefficient estimates together results in the interpretation that valuation inaccuracy after the introduction of ASC 820 decreases to around 13-14%, from 43-50% before the standard. This increase in accuracy is economically very meaningful and can be interpreted that buyout funds' average interim valuations increased to around 87% of the real value of the average investment. This result represents a significant increase in the informativeness of buyout fund interim valuations for the investors.

Table 3 also presents the changes in the "Q4" and "SP500" variables after the introduction of the ASC 820 standard. Results for the changes in the Q4 coefficient are mixed. Although the base specification, column 3, suggests an insignificant change after the standard, we observe a significant decrease when the crisis period is omitted and a significant increase when old observations are dropped. Obviously, very old observations have a boosting effect on the estimate of the "Q4‘ variable, as it has on the "Dist" variable, mainly because of lower quality in valuation practices, which becomes apparent only after an audit or a distribution. And the crisis period observations inhibit the effect of audit on valuations, most probably because of the inability of the auditors to have a clear view of the fair valuations due to the chaotic market conditions. In column 6, in which both effects are eliminated, we observe that the Q4 change in coefficient is statistically insignificant. The change in "ΔSP500" is also statistically insignificant when the effects of old observations and crisis period are eliminated.

	(1)	(2)	(3)	(4)	(5)	(6)
Dist	0.497***	0.505***	0.495***	0.504***	0.430***	0.439***
	(0.053)	(0.055)	(0.053)	(0.056)	(0.077)	(0.083)
Dist x Post	-0.362***	-0.373***	-0.358***	-0.369***	-0.292***	-0.304***
	(0.056)	(0.058)	(0.056)	(0.058)	(0.078)	(0.084)
Q4			0.007**	0.016***	0.001	0.009**
			(0.003)	(0.004)	(0.003)	(0.004)
Q4 x Post			0.003	-0.009**	0.010***	-0.002
			(0.004)	(0.004)	(0.004)	(0.005)
ΔSP500			0.116***	0.049**	0.155***	0.085***
			(0.021)	(0.025)	(0.023)	(0.031)
ΔSP500 x Post			-0.024	0.042	-0.063**	0.003
			(0.023)	(0.029)	(0.025)	(0.034)
Year FE	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES
Observations	25,133	22,314	25,133	22,314	22,944	20,125
Adjusted R^2	0.193	0.203	0.199	0.207	0.174	0.180

Table 3.3: Effects of ASC 820 on Fund Valuations

This table presents the results of panel regressions in which the dependent variable is the quarterly valuation updates of existing fund investments. All models include the quarterly distributions as independent variables whose effects for the period before the introduction of the ASC 820 standard ("Dist") and changes in these effects after ASC 820 ("Dist x Post") are presented separately. All models also include the quarterly capital calls as a control variable, but the results are not tabulated due to their insignificance. All quarterly cash flow data (valuation updates, capital calls and distributions) are normalized as a percentage of the fund size. Models 3 to 6 include the effects of quarterly in S&P 500 returns (ΔSP500) and a dummy variable highlighting fourth quarter observations (Q4) as independent variables. Effects of these variables on valuation updates before and changes in these effects after ASC 820 are reported separately. All model specifications include observation year, fund and fund age (measured in quarters) fixed effects. Models 1 and 3 rely on the full sample. Model 5 filters out the observations before 2000. Models 2, 4 and 6 build on the specifications of their previous columns and eliminate crisis period observations. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the fund firm level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

3.7.3 Valuation Effort after ASC 820

Although the results presented in the last section provide strong evidence supporting the significant increase in valuation accuracy after 2008, it is not enough for us to conclude that this change is attributable to the introduction of ASC 820. In the absence of a control group to compare the change in outcomes (which will be evaluated further in section 7.4) and the existence of the coinciding financial crisis, it can be rightly argued that it is the market-related factors that are driving the increase in valuation accuracy. For example, it can be argued that due to the decrease in asset prices during the crisis, the gap between the book value of PE investments and the actual sales prices may have shrunk, decreasing the valuation inaccuracy temporarily, and this temporary decrease may be the reason we observe such a low coefficient for observations after 2008. Although I have accounted for the possible effects of the financial crisis by eliminating the observations during 2008 and 2009, and I have presented that the results do not change significantly, it may be that the crisis had prolonged effects which went beyond 2009 and caused a significant decrease in the observed effects of distributions on valuation updates. To evaluate this argument, in this section, I analyze (i) the persistence of the improvement in valuation accuracy (ii) the change in fund manager effort to perform better valuations after

ASC 820.

Persistence of the Increase in Valuation Accuracy

If the improvement in valuation accuracy is a result of the temporary changes in the market conditions, we should expect the effects of these market conditions to be eliminated as things turn back to normal. So we should observe the valuation inaccuracy to increase to the levels before the financial crisis. Figure 3 presents the yearly valuation inaccuracy. The dotted line is the yearly valuation inaccuracy, which is the result of a regression based on Equation (5), in which the “Dist” variable is separated into years by multiplying with year indicator variables. Around each yearly coefficient, a 95% confidence interval is reported as solid lines. The figure also highlights the official introduction date of ASC 820, with a vertical dotted line.

Lower bound of the valuation accuracy coefficient is strictly above 0 for all years, highlighting a consistency in the conservative valuation approach for buyout funds. Valuation inaccuracy is high, and it is accompanied by very high volatility before ASC 820. The valuation inaccuracy coefficient only decreases temporarily for a couple of years around the “Dot.com” crisis at around the beginning of the century, which is a direct result of decreased asset prices, reducing the differences between market and book values and artificially pushing the valuation inaccuracy down. After 2008, however, the coefficient and its volatility significantly decrease, settling around the vicinity of 10-20%. Even ten years after the financial crisis, there are no jumps and any signs of reverting to the pre - ASC 820 levels. This figure contradicts the hypothesis that it is the market conditions, but not ASC 820, that affect valuation accuracy after 2008.

Valuation Updates Following Changes in Market Conditions

Figure 4 is a simpler version of Figure 1 which helps us to clearly visualize the relationships between the fund valuation updates and the factors that affect them. We can comment that there are two broad groups of factors that affect fund valuations: Investment-Specific Factors and Market-Related Factors. The value of each investment of the fund is affected by the changes in the market conditions in a similar fashion (e.g. a financial crisis, liquidity squeeze, stock market rally), but they also have different, specific characteristics that affect valuations in entirely different ways (e.g. sector-specific developments, technological advancements, quality of management team).

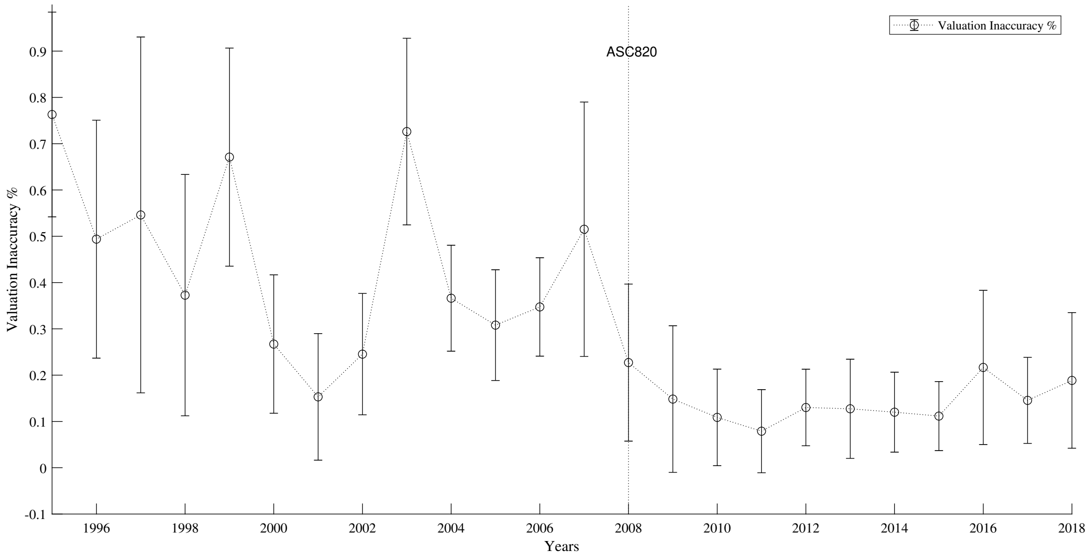

Figure 3.3: Yearly Valuation Inaccuracy

This figure presents the yearly change in fund valuation inaccuracy. Dotted line represents the coefficients of "Dist" variables retrieved from the regression model: $\Delta VAL_{q,i} = \alpha + \beta_1\ CapCall_{q,i} + \beta_2 Dist_{q,i} + \beta_3 \Delta SP500_q + \beta_4 Q4_q + \gamma X_{q,i} + \epsilon_{q,i}$. β_2 coefficients are obtained separately for each year to capture the yearly valuation inaccuracy. Upper and lower boundaries of the 95% confidence interval are presented for the coefficient of each year. The confidence interval is calculated using the heteroskedasticity-robust standard errors clustered at the fund firm level. The dotted vertical line highlights the date ASC 820 standard became fully effective.

If the fund manager does not exert effort to update valuations, routes (1) and (4) in Figure 4 are defunct, and relationships are indirect through distributions. If, on the contrary, the fund manager exerts effort to update valuations such that they incorporate the market-related or investment-specific developments, routes (1) and (4) are promoted over (2) and (3). Previous sections of this paper rely on exploiting route (5) by the model we built in Equation (5). This analysis evaluates if distributions affect fund valuations, and this indirectly tells us how effective routes (2) and (3) are, which is a proxy for valuation inaccuracy. By evaluating routes (3) and (4) of Figure 4, we can learn about the effort exerted by the funds to increase valuation quality. By evaluating the interconnectedness of market returns and valuation inaccuracy, we can comment on the changes in valuation effort.

In the absence of managerial effort for valuation, cumulative effects of lagged market returns will be incorporated into valuations only after a distribution. This would lead to a high correlation between market returns and valuation inaccuracy. Relatedly, if we evaluate the effect of the interaction of distributions with lagged cumulative market returns, we should be observing a significant effect. An increase in effort, however, should significantly decrease these effects. Therefore we can hypothesize that, if manager effort increased after ASC 820 we should observe (i) a decreased correlation between valuation inaccuracy and market returns (ii) a smaller effect of the interaction of distributions and market returns on valuation updates.

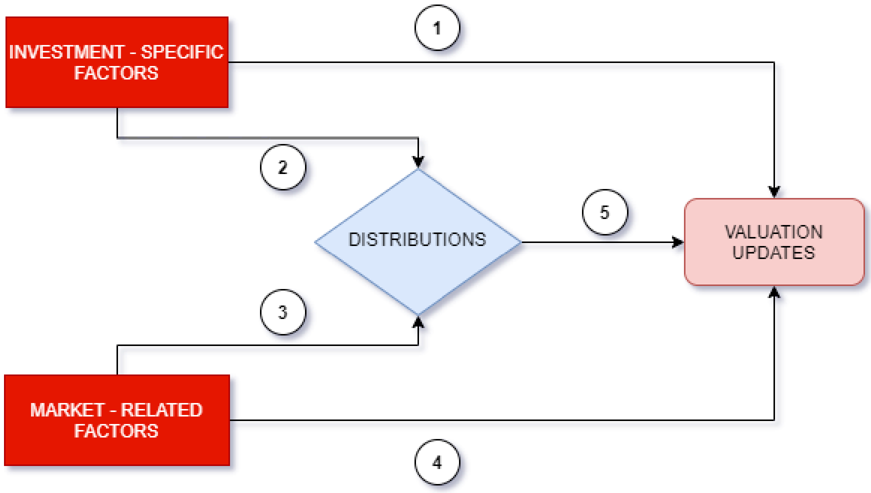

Figure 3.4: Effects of Market Returns on Valuation

This figure illustrates the relationship between fund valuation updates and factors affecting them. Timely and accurate incorporation of the new information regarding these factors promotes a direct relationship, represented by routes (1) and (4) and this relationship results in high valuation accuracy. Failing to do so, however, results in the real economic values of investments being uncovered only after the sale of the investment, in which case routes (2) and (3) are active, and valuation accuracy is low. Therefore evaluating Route (5), the extent of the relationship between distributions and fund valuations is directly informative about the valuation accuracy.

Figure 5 compares yearly valuation inaccuracy coefficients (dashed line) with yearly percentage changes in the S&P 500 index (solid line). The figure poses an apparent relationship between inaccuracy coefficients and S&P 500 returns before 2008, which almost completely dies after 2008. Indeed, the correlation between the market returns and the valuation inaccuracy coefficient decreases from 0.78 before 2008, to only 0.08 after 2008. In this respect, the fact that valuation inaccuracy is no more correlated with the market returns signals the structural change in reporting quality, due to increased valuation effort. The fact that funds better value their investments in accordance with the fair value measurement standard, taking into consideration the changes in market conditions, enhances not only the overall valuation accuracy but also the consistency. If, on the contrary, the change in the valuation accuracy that Table 3 demonstrates was a result of changes in market conditions but not the increased effort by the fund managers to adjust valuations based on the market conditions, we should have been observing the inaccuracy coefficients to continue their co-movement with the market returns.

The next step is to evaluate the effect of the interaction of distribution with market returns on valuation updates. For this test, I introduce a new variable, SP5004Q, which is the change in the S&P500 index during the 1-year period before each observation. As discussed above, under low effort, market-related effects from previous quarters will only be uncovered after a

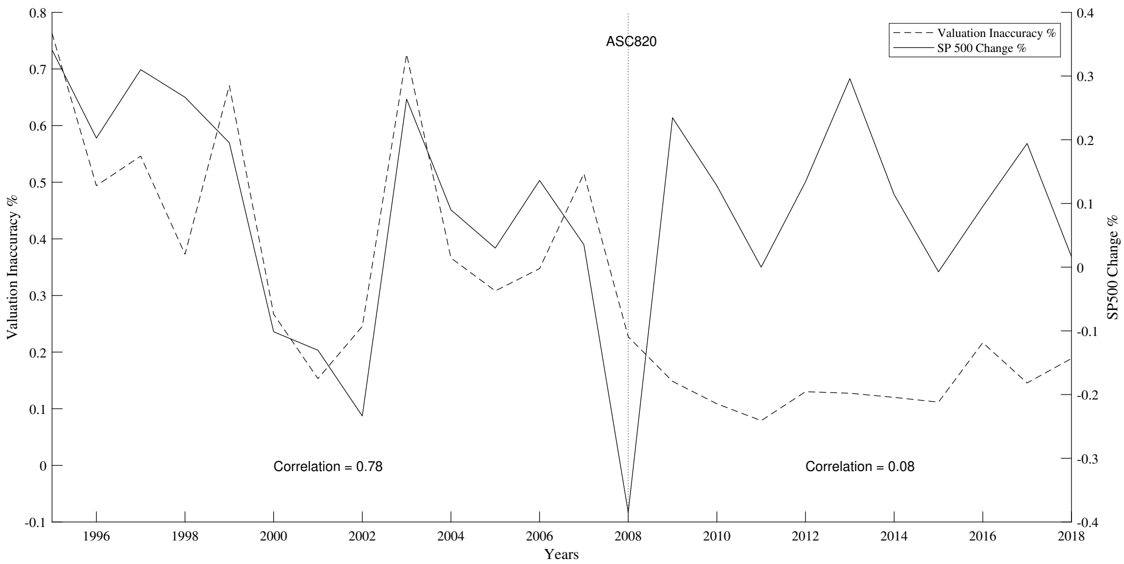

Figure 3.5: Yearly Valuation Inaccuracy vs S&P 500 Returns

This figure presents the relationship between valuation inaccuracy and market returns. The dashed line is plotted on the left vertical axis and it represents the coefficients of "Dist" variables retrieved from the regression model: $\Delta VAL_{q,i} = \alpha + \beta_1 \; CapCall_{q,i} + \beta_2 Dist_{q,i} + \beta_3 \Delta SP500_q + \beta_4 Q4_q + \gamma X_{q,i} + \epsilon_{q,i}$. β_2 coefficients are obtained separately for each year to capture the yearly valuation inaccuracy. The solid line is plotted on the right vertical axis and it represents the yearly return on the S&P 500 index. The dotted vertical line highlights the date ASC 820 standard became fully effective.

distribution. Therefore it is fair to expect the interaction of market returns with distributions to have a positive and significant coefficient. We should, however, see this coefficient decrease after ASC 820. For this test, I build the regression model below:

$$\Delta VAL_{q,i} = \alpha + \beta_1 Dist_{q,i} + \beta_2 SP5004Q_q + \beta_3 Post_q + \beta_4 (Dist_{q,i} \text{ x } Post_q) + \beta_5 (SP5004Q_q \text{ x } Post_q) + \beta_6 (Dist_{q,i} \text{ x } SP5004Q_q) + \beta_7 \; (Dist_{q,i} \text{ x } SP5004Q_q \text{ x } Post_q) + \xi C_{q,i} + \gamma X_{q,i} + \epsilon_{q,i} \qquad (6)$$

In Equation (6), we are particularly interested in coefficients β_6 and β_7, which will reveal the effect of the interaction term on valuations, and change in this effect after the introduction of ASC 820. To capture the effects of these double and triple interactions correctly, the model includes the three root variables and all other interactions of these variables separately. The model also includes capital calls (CapCall) and Q4 dummy (Q4) as control variables (Matrix "C"), on top of fund, age and year fixed effects (Matrix "X").

Table 4 summarizes the results of the test introduced above. Column 1 introduces the model without fixed effects. Column 2 adds these effects. In column 3, I eliminate all observations with zero distributions, to see more clearly the effect of market returns on valuations, when there are distributions to the fund investors. Column 4 eliminates crisis period observations.

The coefficient of the interaction term for observations before the ASC 820 is between 0.64 - 0.80 and statistically significant for all specifications. This means that before 2008, funds were failing to incorporate even very old changes appropriately in market prices. This finding is compatible with the industry practices of keeping investments at the historical cost until they are sold or limiting valuation updates to restrict high NAV volatility, which means that before ASC 820, fund managers were exerting limited effort to have highly informative valuations.

The coefficient for the "Dist" variable before 2008 is between 36.4 - 44.7%, decreasing by around 5 - 13% compared to the model (3) in Table 3, with the introduction of the interaction term. This tells us that 10 - 25% of the valuation inaccuracy is sourced from a lack of effort to update the valuations of existing investments based on market conditions, and the remaining valuation inaccuracy can be attributed to factors specific to the investment.

The last term in Table 4 evaluates the change in the coefficient of the interaction term after ASC 820, and as the results suggest the situation completely changes after 2008. The coefficients significantly decrease after ASC 820 and become statistically indistinguishable from 0 for all specifications (not tabulated). This means that funds have taken actions to update the valuations of their existing investments based on the developments in the market, and the need to further adjust the valuation at the date of the sale of investment is limited to the idiosyncratic value changes that could not be estimated correctly. These results are completely in line with the hypothesis laid out in the previous paragraphs, and the analysis made using Figure 5. This analysis clearly shows that the increase in valuation accuracy after 2008 is not sourced by a market-related factor, but is a result of the introduction of ASC 820 which pushed the valuation efforts upwards.

3.7.4 Interim Valuations and Fund Geography

The empirical analysis presented until now has the implicit assumption that ASC 820, which is published for funds located in the US, affects American and European funds similarly. In reality, European funds might be reacting not to ASC 820, but to another standard, IFRS 13, which was published four years after ASC 820 and specifically targeted European funds. The distinction is irrelevant to our main empirical question since both of them are fair value measurement standards, and they are equivalent in content. However, evaluating the reaction of funds located in both geographies to these different standards is important. The private equity industry is globally highly integrated, with very large institutional investors diversifying their private equity portfolios by investing in funds in different countries. These investors are known to be demanding the valuations of their investments to be updated following state-of-the-art accounting principles. Evaluating the interim valuation inaccuracy separately for the US and Europe funds would be informative on the extent of (1) the global integration of the private equity industry evaluated through the global effects of local changes (2) the disclosure spill-over

	(1)	(2)	(3)	(4)
Dist	0.447***	0.405***	0.396***	0.364***
	(0.049)	(0.053)	(0.050)	(0.063)
SP5004Q	0.075***	0.021	-0.020	0.034*
	(0.008)	(0.014)	(0.024)	(0.018)
Post	0.013***	-0.059***	-0.070***	-0.055***
	(0.002)	(0.007)	(0.014)	(0.008)
Dist x Post	-0.278***	-0.271***	-0.278***	-0.228***
	(0.058)	(0.062)	(0.056)	(0.070)
SP5004Q x Post	-0.029***	0.027*	0.078***	0.014
	(0.009)	(0.015)	(0.026)	(0.020)
Dist x SP5004Q	0.644**	0.758***	0.802***	0.785**
	(0.254)	(0.254)	(0.277)	(0.355)
Dist x SP5004Q x Post	-0.578*	-0.742**	-0.714**	-0.771**
	(0.302)	(0.309)	(0.319)	(0.395)
Year FE	NO	YES	YES	YES
Fund FE	NO	YES	YES	YES
Age FE	NO	YES	YES	YES
Additional Controls	YES	YES	YES	YES
Observations	25,133	25,133	11,732	22,944
Adjusted R^2	0.194	0.206	0.335	0.179

Table 3.4: Effects of Market Conditions on Fund Valuations through Distributions

This table presents the results of the regressions which aim to evaluate the relationship between the interaction of "Dist" (quarterly distributions) and "SP5004Q" (change in S&P500 index for the last four quarters as of the observation date), and the valuation updates. "Dist x SP5004Q" evaluates this relationship for the period before ASC 820, and "Dist x SP5004Q x Post" does it for the period after. The model also includes all three root variables and other interactions. All models also include capital calls (CapCall) and an indicator variable highlighting the 4th quarter observations (Q4) as additional control variables. Columns 2-4 include year, fund and age fixed effects. Columns 1 and 2 are based on the full sample. Column 3 eliminates observations without distributions. Column 4 eliminates crisis-period observations. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the fund firm level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

effects in the private equity industry (3) the power of fund investors, on imposing their demands to fund managers.

Figure 6 presents the yearly valuation inaccuracy coefficients separately for American and European funds. The yearly patterns suggest that the valuation accuracy of funds located in the US and Europe evolve in a very similar fashion. Temporary improvements during the two financial crises follow very high inaccuracy levels before the 2000s. Finally, a permanent enhancement is reached after the introduction of ASC 820. Also, the inaccuracy levels in Europe seem to have already been settled to a lower level before the introduction of IFRS 13, the European equivalent of ASC 820.

An analytical evaluation of the effect of ASC 820 on the valuation accuracy of the funds in different geographies is presented in Table 5. The four panels lay out the results of the regressions in which the valuation inaccuracy is separately evaluated for US and Europe funds. The tables also include the diff-in-diff estimators in the right-bottom corner of the upper blocks of all panels. In Panel A, which utilizes the full sample, we observe that the valuation accuracy of both American and European funds significantly improve after 2008. The negative (but statistically insignificant) difference before 2008 between the US and Europe may be associated with the introduction of IAS 39 in Europe. After 2008, however, the coefficients for both

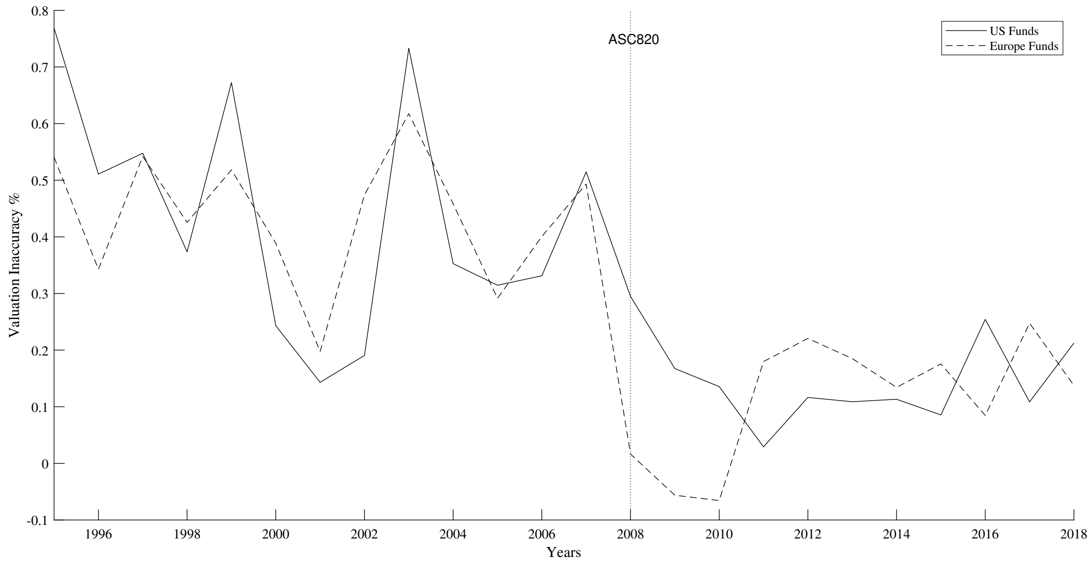

Figure 3.6: Yearly Valuation Inaccuracy - American vs European Funds

This figure presents the yearly valuation inaccuracy, separately for private equity funds located in the United States and Europe. Coefficients of "Dist" variables retrieved from the regression model: $\Delta VAL_{q,i} = \alpha + \beta_1\ CapCall_{q,i} + \beta_2 Dist_{q,i} + \beta_3 \Delta SP500_q + \beta_4 Q4_q + \gamma X_{q,i} + \epsilon_{q,i}$. β_2 coefficients are obtained separately for each year to capture the yearly valuation inaccuracy. The solid black line represents the yearly valuation inaccuracy of the funds located in the United States, and the dashed line plots the coefficients for European funds. The dotted vertical line highlights the date ASC 820 standard became fully effective.

countries converge to levels that are economically and statistically indistinguishable. Although the diff-in-diff effect is economically sizeable, it is statistically insignificant. Of course, since this panel works with the full sample, changes after 2008 can be attributed to both FVM standards, ASC 820 and IFRS13. Overall, Panel A shows us that funds located in the US and Europe are affected by the two FVM standards similarly.

Do FVM standards in different countries create a spill-over effect, or do the funds react only to the changes in the geography that they are located? Panel B and C of Table 5 help us to evaluate this question by zooming to a restricted sample of observations, four years before and after ASC 820 and IFRS 13. The window is specified as four years to appropriately capture the period between ASC 820 (Nov 2008) and IFRS 13 (Jan 2013). In Panel B, we observe that the reaction of US and Europe funds to ASC 820 is almost identical, with significant improvement in the valuation accuracy for both groups, and an insignificant diff-in-diff coefficient. Although it is not possible to disentangle the effects of the financial crisis on these results, assuming that the two developed geographies are affected by the crisis in a similar way, we can conclude that the European Funds reacts to the ASC 820 standard of the US very similar to the US funds. In Panel C, we move one step forward to evaluate the reaction to IFRS 13 standard by the funds. For this test only, the indicator variable "Post" takes a value of 1 if the observation is after the introduction of IFRS 13 (Jan 2013) and 0 otherwise. A similar evaluation shows us that there is no significant reaction to IFRS 13 from both fund groups and the changes in valuation accuracy are statistically indistinguishable from 0. Using these results, we can conclude that the European funds acted proactively by adapting to the FVM standard of the US long before the official introduction of IFRS 13.

The results presented in Panels A to C of Table 5 support the observations made using Figure 5. Although ASC 820 is introduced in the US, it also affected European funds with a similar intensity. This finding is surprising yet understandable, and the possible reasons are related to some of the discussions made in this paper in different sections. Firstly, a significant number of private equity fund firms operate globally, with a large number of individual funds in the US and Europe, and it is plausible to think that they may have preferred to apply an updated valuation method to all of their funds simultaneously. Secondly, European funds may have felt “Peer Pressure”, i.e. the fact that they appeal to the same investor pool, they may have felt the need to put better valuation practices into effect. Finally, the investors of private equity funds are large financial institutions, which mostly have the power to dictate their preferences to the fund managers in terms of the valuations they will receive quarterly. Even if the fund invested is in Europe, these investors may have had the appetite to ask for interim valuations that can be comparable to the ones they receive for the invested US funds.

To test the first two explanations mentioned in the previous paragraph, I focus on funds operating in Europe, and classify them as “Global Firms” and “Local Firms”. To do this classification, I obtain the list of private equity fund firms from Bloomberg Professional Terminal, separately for firms operating only in Europe and both in Europe and the US. I then match the firm names with the Cash Flow database of Preqin. Based on this information, I classify the European funds into one of the two groups introduced above. If the reason for better valuations in Europe is the centralized practices of global PE firms, I should be observing a significant difference-in-differences effect between funds of global and local fund firms. The absence of such an effect would mean that even the funds without an organic connection to the United States adopted the valuation methodologies introduced by ASC 820.

Panel D presents the results of the test comparing the changes in valuation accuracy between the funds of global and local fund firms. The test focuses only on the European funds, and the four years window before and after ASC 820. These limitations significantly decrease the number of observations and the coefficient significance obtained, but the results are still meaningful. First, We observe that global fund firms have better valuation quality compared to the local ones, both before and after ASC 820. This result is not surprising given the possible differences in investor profiles, organization sizes, and resources that can be allocated to investment valuation. Nevertheless, ASC 820 affects both European firm types similarly, significantly decreasing the valuation inaccuracy coefficients, without a significant diff-in-diff coefficient. These results are robust to the alternative test in which all observations during the financial crisis are eliminated. So, even the fund firms that have operations only in Europe improve valuation practices following the introduction of ASC 820. This finding constitutes support for "Peer Pressure" effect. Given the fact that all private equity funds race to get investment from the same pool of highly-sophisticated institutional investors, the fact that a significant number of funds will produce higher-quality valuations puts pressure on others to voluntarily improve their disclosure quality.

3.7.5 Interim Valuations and LP Power

The previous section concluded with a discussion of the possible reasons for the ASC 820 standard affecting the European funds with a similar magnitude compared to the US funds. This discussion leads us to a related question regarding the relationship between funds and their investors: How does the existence of powerful investors affect the interim fund valuation accuracy? It is discussed before that large pension funds ("LPF") have an activist approach. As Easton, Larocque, and Stevens (2018) state, pension funds tend to include a clause to the partnership agreement, requiring the GPs to comply with the local GAAP. Pension funds are known to go as far as suspending commitments to specific funds until the funds accept their demands (Indap, 2018). So it may be possible that the existence of LPFs as investors create an incentive for the fund managers to increase their efforts towards better valuations. Comparison of the valuation accuracy of funds that receive investments from large pension funds with the ones that do not can tell us about the power of investors over fund managers.

Panel A: Full Sample	US	Europe	Δ
Dist	0.506***	0.419***	-0.087
	(0.057)	(0.080)	(0.095)
Dist x Post	-0.378***	-0.253***	0.125
	(0.061)	(0.094)	(0.106)
Year FE	YES	YES	-
Fund FE	YES	YES	-
Age FE	YES	YES	-
Additional Controls	YES	YES	-
Observations	19,352	5,781	-
Adjusted R^2	0.199	0.190	-
Panel B: 4-Year Window (ASC820)	**US**	**Europe**	**Δ**
Dist	0.427***	0.429***	-0.003
	(0.115)	(0.115)	(0.153)
Dist x Post	-0.330***	-0.305*	0.025
	(0.117)	(0.158)	(0.177)
Year FE	YES	YES	-
Fund FE	YES	YES	-
Age FE	YES	YES	-
Additional Controls	YES	YES	-
Observations	8,146	2,385	-
Adjusted R^2	0.207	0.241	-
Panel C: 4-Year Window (IFRS13)	**US**	**Europe**	**Δ**
Dist	0.103***	0.164**	0.061
	(0.027)	(0.072)	(0.073)
Dist x Post	0.032	-0.027	-0.059
	(0.042)	(0.070)	(0.076)
Year FE	YES	YES	-
Fund FE	YES	YES	-
Age FE	YES	YES	-
Additional Controls	YES	YES	-
Observations	9,818	3,651	-
Adjusted R^2	0.116	0.144	-
Panel D: 4-Year Window (ASC820)	**Local Firms**	**Global Firms**	**Δ**
Dist	0.452***	0.228***	-0.224*
	(0.134)	(0.074)	(0.127)
Dist x Post	-0.283*	-0.231	0.052
	(0.172)	(0.171)	(0.179)
Year FE	YES	YES	-
Fund FE	YES	YES	-
Age FE	YES	YES	-
Additional Controls	YES	YES	-
Observations	1,769	616	-
R-squared	0.246	0.222	-

Table 3.5: Fund Valuations and Geography

This table presents the results of the regressions that evaluate the valuation inaccuracy separately for funds located in the United States and Europe. Differences between the countries are also presented. In all regressions, the dependent variable is the quarterly valuation updates. All four panels rely on the same specification. In Panels A, B and D, the coefficient of "Dist" captures the valuation inaccuracy before ASC 820, and "Dist x Post" presents the change after the standard. In Panel C, the same evaluation is done for IFRS 13 standard. All regressions include capital calls (CapCall), changes in S&P500 index (ΔSP500) and an indicator variable highlighting the observations in fourth quarters (Q4) as additional control variables. All models also include year, fund and age fixed effects. Panel A relies on the full sample. Panels B and D focus on the four-year window before/after ASC 820. Panel C focuses on the four-year window before/after IFRS 13. Panel D evaluates the European funds belonging to global/local fund firms separately.

Identification of the causal effect of having LPFs as investors on fund valuation, however, has several potential difficulties. First, funds invested by LPFs may have structural differences compared to the others. For example, they may have larger sizes, which would mean larger organizations and better opportunities for high-quality valuation. Alternatively, these funds may be of higher performance, which may signal fund quality and will mean LPFs have superior fund-selection skills. In these cases, any possible significant relationship found between investor strength and valuation accuracy may be a result of reverse causality, i.e., funds invested by large investors may be the ones with high valuation quality in the first place. Second, vintages of the funds invested by LPFs may differ from the others, and in the existence of structural changes in valuation accuracy in time due to Fair Value Measurement standards, it might heavily bias the coefficients obtained. Third, LPF-invested funds may differ structurally in terms of being a first-time or follow-on fund. A first-time fund is the first fund of a fund firm. Given the need for this fund firm to engage with higher-quality investors, it might be expected for these funds to be more susceptible to take action following the investors' demands. Finally, funds that receive LPF investment may be more concentrated in a specific geographical area, the US or Europe, which may bias the treatment effects.

To shed light on the question above, I collect additional data on the private equity investments of 29 out of 36 public pension funds located in either US or Canada that are classified among the top 100 LPs globally. These pension funds have a combined AUM of \$2.9 trillion, of which \$305 billion is allocated to private equity investments (Preqin, 2017). Unlike other types of private equity investors, most of the large public pension funds ("LPFs") located in the United States publish the details of their investments regularly since these public institutions are bound by state laws and the Freedom of Information Act ("FOIA"), regarding sharing information with the public. For the private equity investments, details of the shared data mostly include the name of the fund committed, commitment amount and value of the remaining invested capital. This data is available to be obtained from Bloomberg Professional Terminal, separately for each public pension fund which shared the investment details with the public. Since this analysis aims to evaluate the relationship between having strong public pension funds as investors and interim valuation accuracy, collected data on pension fund investments is matched with the Preqin cash flow data that is used throughout the analysis. Around half of the buyout funds included in the valuation accuracy analysis have been invested by at least one of the large pension funds included in the dataset.

Panel A of Table 6 briefly presents the characteristics of the private equity funds invested by large public pension funds separately for the US and Europe and compares these characteristics with that of the funds that are not invested by these pension funds. "LPF = 1" stands for the funds invested by at least one large pension fund, and "LPF = 0" is for the others. We can observe in the table that on average, LPFs invest in funds with more recent vintages for both geographies. It is known that the popularity of private equity investment by public pension funds follows the exceptional success of university endowment funds' private equity investments and allocation to private equity booms after the financial crisis. Ivashina and Lerner (2018) show that US public pension funds' allocation as a percentage of their AUM increases from 7.4% in 2008 to 19.6% in 2017. These facts explain why pension fund investments are focused on funds with more recent vintages. The second and third lines of the table compare the sizes of the funds invested by LPFs to the others. In both countries, the mean size of these funds is more than triple of the other funds. Since this result may simply be because LPFs invest in more recent funds, I also assess the size difference in a standardized method. For each vintage, I calculate the median fund size, and I build an indicator variable which takes the value of 1 if a fund's size is above the median size of its vintage and 0 otherwise. The results of this comparison are reported in line 3. For both countries, the probability for an LPF - invested fund to have an above-median size is double of other funds. This is in line with Da Rin and Phalippou (2017) who show that large private equity fund size is a decisive selection criterion for large LPs since the fund size is seen as a signal for fund quality and reputation.

The fourth and fifth lines of Panel A compare the percentage of first-time funds among the funds that received and did not receive LPF investment. We observe that the LPF investment percentage in first-time funds is significantly less. A possible reason might be seeking a track record as a signal for quality before committing to a fund. The sizes of these first-time funds that receive LPF investment, however, are not statistically different from the average.

In the sixth line of Panel A, we can observe the average Public Market Equivalent ("PME") of the funds. PME is a fund performance metric introduced by Kaplan and Schoar (2005) as an alternative to the absolute performance metrics, such as IRR and multiples, that are extensively used in the private equity industry in the absence of an appropriate risk-adjusting mechanism. PME is the ratio of the present value of fund cash inflows to outflows, discounted by the returns of an appropriate market index (S&P 500 in this study). This metric inherently assumes a fund beta of 1 for all funds, so it is not entirely able to capture the riskiness of private equity investments, but in the absence of active market valuation that limits the possibility of applying factor models to risk-adjust the fund returns, it is an important step forward compared to the absolute performance metrics; therefore it is extensively used in academic research. On average, the funds that the LPFs invest underperform compared to the other funds, both in the US and Europe. However, there is an important caveat here that needs to be considered. As discussed above, LPF investments are focused on the funds with later vintages. These funds will have a much higher proportion of investments that are not liquidated, and the fund itself does the valuation of these investments, so these valuations are susceptible to being affected by the valuation errors (under-valuation, on average) discussed in Section 6 of this paper. But even eliminating the funds with vintages after 2012 gives similar results. These results are in line with Hochberg and Rauh (2013) and Sensoy, Wang and Weisbach (2014), which find under-performance and no over-performance for pension fund investments respectively, compared to other types of LPs. To summarize the data presented in Panel A of Table 6, on average LPFs invest in funds belonging to more experienced fund firms, with recent vintages, larger sizes and no over-performance. These patterns are very similar for investments in the US and Europe.

Panel B of Table 6 summarizes the investment characteristics of LPFs, focusing only on the private equity funds that receive investments from at least one LPF. The average LPF-invested fund receives investments from 4 LPFs, and the average LPF investment to a PE fund is close to $100 million. These two figures are very close for US and Europe funds. Since the funds invested in Europe have a larger size, these investment levels lead to a smaller share of LPF ownership in European funds. Still, LPF ownership percentages of invested funds in the US and Europe are economically close, meaning that overall, LPFs have very similar investment patterns in the United States and Europe.

Panel A: Characteristics of the Committed PE Funds

	United States			Europe		
	LPF = 1	LPF = 0	Difference	LPF = 1	LPF = 0	Difference
Vintage	2010.1	2002.9	7.2***	2010.7	2008.2	2.6***
Size	2,588	704	1,884***	3,468	915	2,553***
% of Size > Median	0.64	0.32	0.33***	0.75	0.34	0.42***
% FTF	0.08	0.20	-0.12***	0.04	0.10	-0.05
Size - FTF	593	450	143	590	749	-160
PME	1.23	1.30	-0.07*	1.12	1.27	-0.15**
PME (Vintage < 2012)	1.27	1.35	-0.08	1.11	1.31	-0.2**
PME - FTF	1.20	1.32	-0.12	1.21	1.35	-0.14
No. of Funds	361	389	-	113	148	-

Panel B: Characteristics of Commitments

LPF = 1	United States	Europe	Difference
LPF count	3.9	4.0	-0.1
LPF investment (mil. USD)	95.2	107.9	-12.7
LPF share	18.0%	13.8%	4.3%***
No. of Funds	361	113	-

Table 3.6: Descriptive Statistics - Commitments of Large Pension Funds

This table presents the descriptive statistics for the buyout fund commitments of large pension funds. The table presents the data separately for funds located in the United States and Europe. Panel A compares the characteristics of the PE funds, that receive/do not receive investment from large pension funds. “LPF = 1 ” stands for the funds which received investments from at least one large pension fund, and “LPF = 0” are the rest. “Vintage” is the year the fund started operation. “Size” is the total amount of commitment secured from the investors. “% of Size > Median” is the percentage of the funds that has a size greater than the median size of the same vintage. “% FTF” is the percentage of first-time funds (first fund of a fund firm). PME is a performance metric which is the ratio of the present value of proceeds to the present value of investments, all discounted by the return in S&P 500 index. “PME (Vintage < 2012)” only focuses on funds with vintages before 2012. “PME - FTF” presents the PMEs of FTFs. Panel B presents the characteristics of the commitments of large pension funds. “LPF Count” is the average number of LPFs, investing in a fund. “LPF Investment” is the average LPF commitment in a fund. “LPF Share” is the average share of total LPF commitment in the fund.

Assessing the causal effects of having an LPF as an investor on the valuation quality will yield biased results as long as the very significant structural differences between the private equity funds that receive LPF investment and others are not accounted for. As discussed before, observable characteristics such as fund vintage, size, sequence (first-time vs follow-on) and geography might be affecting valuation quality. On top of these observables, unobservable characteristics such as fund ability or the quality of the management team might also be among the factors determining the valuation quality. To overcome the challenges related to the differences in observed fund characteristics, I apply the propensity score matching methodology.

Since propensity score matching is a selection-on-observables method, it can not account for the differences that originate from the unobservable characteristics. To account for this problem, as a first step, I only keep the fund firms that have at least one fund with LPF investment, and one fund with no LPF investment in the database. By doing so I make sure that all of the fund firms are "players of the same league", i.e. they possess a certain level of quality to attract large investors. Limiting the database to these fund families, and evaluating the differences between their LPF invested and non-LPF invested funds would significantly alleviate the effects related to the unobserved characteristics such as fund ability. This filtering leaves 460 buyout funds in the sample.

In the second step, I follow Rosenbaum and Rubin (1983, 1985) and calculate a propensity score for each fund in the sample based on the observable characteristics (Vintage, Size, Sequence and Geography), using a logit model. I define the LPF investment in a fund as the treatment, hence I classify the funds with LPF investment as the treatment group and the others as the control group. Using the calculated propensity scores, I match the funds in each group based on the "Calipher Matching" methodology. Given the very limited number of observable characteristics that the matching relies on, I set a very small calipher (0.0001), to be able to sustain a balance in the observable characteristics of the matched treatment and control groups. This calipher level is much smaller compared to the levels proposed as 0.2σ of propensity scores by Cochran and Rubin (1973). This methodology results in a matching of 100 funds in total, 50 matched funds for each of the treatment and control groups, with a total of 2,852 quarter observations.

Figure 7 presents the balance of the observable fund and observation characteristics between the treatment and control groups, among the matched sample of 100 funds. White markers are for the differences before the matching, and black markers represent the balance after the matching. In accordance with the dominant approach for the evaluation of the balance in the propensity score matching literature, I present the balance as the standardized mean difference for each variable, calculated as the difference between the mean values of each variable between the treatment and control groups, divided to the standard deviation of the variables for the treatment group. Variables above the horizontal black line are the fund-level variables, and the ones below the line are observation-level variables. Vertical dot lines represent the acceptable limits for the standardized differences. Although Rubin (2001) and Stuart (2010) propose an absolute limit of 0.25 for each observed variable, I apply a more conservative limit of 0.10, consistent with the empirical literature.

Figure 7 shows that before fund matching, there are very significant differences between the treatment and control groups. Apart from the significant differences in fund vintage, size, geography and sequence, which were already discussed in Table 6, there are significant differences in related observation-level characteristics. In connection with the fund vintage difference, treated observations are more concentrated on the period after the introduction of ASC 820. These observations also have a slightly lower mean of fund age. Based on the specifications discussed in the previous paragraph, we can comment that the propensity score matching does a good job of balancing the observable characteristics of the treatment and control groups. Almost all of the variables come close to a perfect balance after matching, and only one of them, fund size, is marginally out of the conservative limits used. However, this difference in fund size is economically insignificant (1,600 vs 1,400m USD). As a conservative approach, I run additional regressions (not tabulated) to analyze the effect of fund size on valuation accuracy and observe no significant relationship. This finding decreases the chance that the minor imbalance between the treatment and control groups in terms of the fund size poses a threat to the analysis that will be made using the matched sample.

Since a healthy analysis of the effects of LPF investment in funds before and after ASC 820 strictly relies on a balanced sample based on the observation years, it is crucial to make sure that not only the mean but also the distribution of observation years is balanced after the matching procedure. Figure 8 presents the related comparisons for the initial sample, for the intermediary sample in which the fund firms with no LPF investments are filtered out, and the final sample after propensity score matching. The figure makes it evident that the initial sample is highly imbalanced in terms of the observation years, with treatment observations highly concentrated in the period after 2000. A significant percentage of the control observations, however, belong to the period before 2000. The initial filtering step partially accounts for this imbalance but is still not adequate to end up with a sample that can alleviate the concerns regarding the

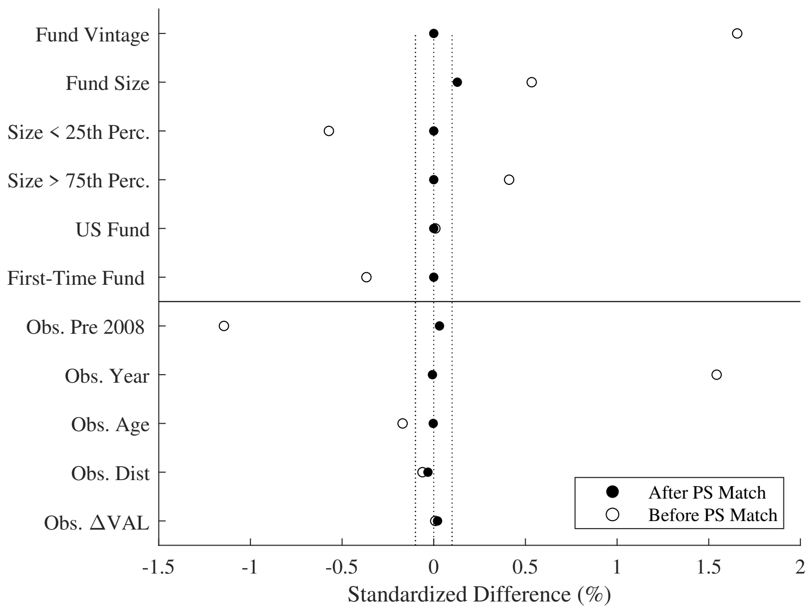

Figure 3.7: Comparison of Observable Characteristics - Before vs After Matching

This figure plots the differences in the observable characteristics between the treatment group (buyout funds that received investment from at least one large pension fund) and the control group (buyout funds that did not receive investment from any large pension fund). Fund-level characteristics are the ones above the horizontal black line, and observation-level characteristics are below the line. Differences are standardized. White markers represent the differences before matching, and black markers are for the ones after. Vertical dotted lines draw acceptable limits for the standardized differences.

difference in the distribution of observation years between treatment and control groups. After propensity score matching, however, we end up with a good balance, which, on top of the analysis made using Figure 7, significantly increases the reliability of the analysis that will be done using the matched sample.

The first question to be answered is the causal effect of having an LPF as an investor on the valuation accuracy. The specification of the tests is:

$$\Delta VAL_{q,i} = \alpha + \beta_1(Dist_{q,i}) + \beta_2(Dist_{q,i} \text{ x } LPF_i) + \beta_3(Dist_{q,i} \text{ x } Post_q) + \beta_4(Dist_{q,i} \text{ x } Post_q \text{ x } LPF_i) + \xi C_{q,i} + \gamma X_{q,i} + \epsilon_{q,i} \tag{7}$$

The "Post" dummy takes the value of 1 if the observation belongs to the period after ASC 820 and 0 otherwise. The dummy variable "LPF" represents the treatment effect of having a large pension fund as an investor. Matrix "C" stands for the additional control variables which are not tabulated (CapCall, SP500, Q4). Matrix "X" represents the fixed effects (Age, Year, Fund).

Table 7 presents the results. The first column uses the full, unbalanced sample. The second column filters out the fund families that did not receive an investment from LPF funds. The third column uses the sample matched by propensity scores. Line 1 and 2 compares the valuation accuracy for the period

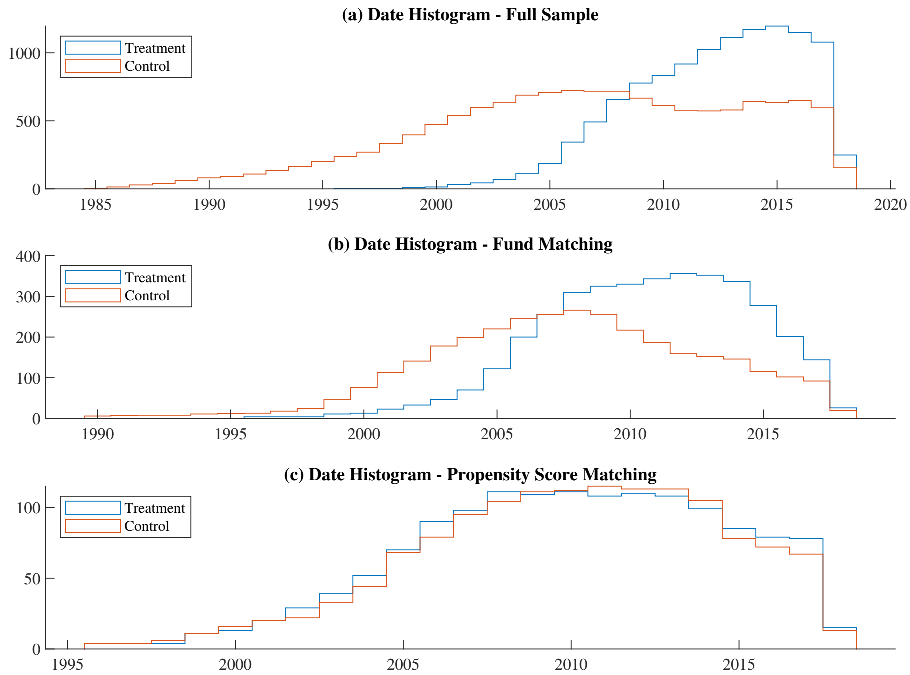

Figure 3.8: Date Distributions - Treatment vs Control Group Observations

This figure presents the balance between the treatment group (buyout funds that received investment from at least one large pension fund) and the control group (buyout funds that did not receive investment from any large pension fund) in terms of observation year. Plot (a) evaluates the balance of the full sample. Plot (b) evaluates the balance after the elimination of fund firms that never received investment from large pension funds for any of their funds. Plot (c) evaluates the balance after propensity score matching.

before ASC 820. We observe that although the unbalanced full sample does not highlight a significant effect of LPF investment on fund valuation accuracy, we observe a highly significant coefficient after matching. These results are not driven by any extreme observations since I perform the same test by eliminating the largest and smallest 1% of observations based on their Dist and ΔVAL variables and obtain similar results (not tabulated). Bearing in mind the fact that our matched sample only consists of the observations from the fund firms that have a history of receiving LPF investments, this finding can be interpreted as evidence that the existence of a large public pension fund as an investment acts as a disciplinary mechanism, pushing the fund manager to exert effort to publish more accurate quarterly valuations.

In Lines 3 and 4, we observe the results for the period after ASC 820. Together with the increase in the overall valuation accuracy after ASC 820, which has already been extensively discussed in this paper, we observe that the effect of LPF on valuation accuracy vanishes. So basically the role played by LPFs in terms of increasing the valuation accuracy before 2008 was undertaken by ASC 820 afterwards. This finding is strong evidence that ASC 820 results in standardization in valuation quality, eliminating the cross-sectional differences among funds with different attributes.

	Full Sample	Firm Filter	PS Match
Dist	0.502***	0.515***	0.507***
	(0.054)	(0.120)	(0.149)
Dist x LPF	-0.138	-0.303***	-0.381**
	(0.105)	(0.118)	(0.149)
Dist x Post	0.156***	0.147***	0.111**
	(0.028)	(0.051)	(0.048)
Dist x LPF x Post	-0.032	-0.031	0.089
	(0.036)	(0.054)	(0.152)
Year FE	YES	YES	YES
Fund FE	YES	YES	YES
Age FE	YES	YES	YES
Additional Controls	YES	YES	YES
Observations	25,133	7,079	2,852
Adj. R^2	0.199	0.219	0.112

Table 3.7: Effects of Large Pension Fund Commitments on Fund Valuation Accuracy

This table presents the results of panel regressions in which the dependent variable is the quarterly valuation updates. coefficient of "Dist" evaluates the valuation accuracy of funds in the control group (not invested by large pension funds) and "Dist x LPF" presents the treatment effect (receiving investment from a large pension fund), before ASC 820. "Dist x LPF x Post" assesses the same treatment effect for the period after ASC 820. Column 1 relies on the full sample. Column 2 eliminates the fund firms that did not receive a commitment from large pension funds for any of their funds. Column 3 is based on the matched sample based on propensity score matching. All regressions include capital calls (CapCall), changes in S&P500 index (ΔSP500) and an indicator variable highlighting the observations in fourth quarters (Q4) as additional control variables. All models also include year, fund and age fixed effects. All standard errors (presented in parentheses) are heteroskedasticity-robust and clustered at the fund firm level. *, **, and *** stands for statistical significance at 10%, 5% and 1% respectively.

Another possible effect of having an LPF as an investor on valuation effort may be observed by evaluating the valuation updates for the quarter observations without distributions. In the absence of distributions, changes in valuations simply represent the updates in valuations of the existing investments. Moreover, a valuation update of "0" basically means that the fund manager sees no reason to exert effort to provide an updated valuation to the investors for that quarter. We can hypothesize that in the presence of LPFs as investors, fund managers may have a greater incentive to update valuations, independent of their accuracy. To test this hypothesis, I build the following linear probability model:

$$ZeroVAL_{q,i} = \alpha + \beta_1 LPF_i + \xi C_{q,i} + \gamma X_{q,i} + \epsilon_{q,i} \tag{8}$$

ZeroVAL is an indicator variable that takes the value of 1 if the absolute valuation update for fund i at quarter q is smaller than 0.1% of the fund size. By defining such a threshold instead of just using 0 valuations, I aim to take into account the changes due to rounding. Variable LPF takes the value of 1 for funds with LPF investment and 0 otherwise. Matrix C includes the untabulated control variables (SP500, Q4), and Matrix X represents the fixed effects (Age, Year).

Although the econometrics literature shows that non-linear models such as probit or logit provide a better fit for the case where the dependent variable is binary, I follow the evaluation made by Angrist and Pischke (2009), which discuss that although non-linear models provide a better fit at the extremes, the average treatment effect captured by linear and non-linear models are similar. Moreover, the coefficients of the linear models are much easier to interpret and clustering the standard errors is less problematic. In light of this discussion, I move on with the linear probability model and present the results in Table 8. The table reports a coefficient for the LPF variable between 4.5% - 5.6%. Given the fact that 14.3% of observations for non-LPF funds have 0 valuation updates, the coefficients mentioned above mean a decrease of 32-39% in the number of observations without valuation updates for LPF funds, which is economically highly significant. Although the statistical significance is at 10% level because of the significantly decreased sample size, these findings provide some additional support to the comments made using Table 7, with the conclusion that having LPFs as investors increase the valuation effort exerted by private equity fund managers.

	(1)	(2)	(3)	(4)
LPF	-0.056**	-0.051*	-0.047*	-0.045*
	(0.028)	(0.027)	(0.025)	(0.025)
Age FE	NO	NO	NO	YES
Year FE	NO	NO	YES	YES
Additional Controls	NO	YES	YES	YES
Observations	1,482	1,482	1,482	1,482
Adj. R^2	0.007	0.013	0.031	0.034

Table 3.8: Effects of Large Pension Fund Commitments on Fund Valuation Effort

This table presents the results of the regressions based on a linear probability model in which the dependent variable is an indicator variable which takes the value of 1 if the absolute valuation update exceeds 0.1% of fund size, and 0 otherwise. LPF is an indicator variable highlighting the observations of funds that receive investments from large pension funds. All regressions rely on the sample matched with propensity score methodology, and all observations without distributions are eliminated. Additional control variables are changes in S&P500 index (ΔSP500) and an indicator variable highlighting the observations in the fourth quarters (Q4).

3.8 Conclusions

This paper analyzes the contribution of fair value measurement standards to private equity fund interim valuation accuracy. This question has significance since interim fund valuations play a major role in the portfolio allocation decisions of investors.

First, I show that the introduction of ASC 820 significantly increases the quality of interim valuations performed by private equity fund managers. Valuation accuracy significantly increases (inaccuracy coefficient decreases from 49% to 14%) after the introduction of the ASC 820 fair value measurement standard. I demonstrate that this decrease is not one-off or temporary; on the contrary, the coefficient is consistently small and moves in a narrow band after the introduction of the standard.

Second, I present that the increase in valuation accuracy is a consequence of the increased valuation effort by the fund managers. To do this, I first compare the valuation inaccuracy coefficients with yearly market returns and show that the strong correlation disappears after the introduction of the standard. I also show that the term that interacts market returns with distributions loses its explanatory power over fund valuations, which infers that fund managers actively incorporate market-related news into valuations.

Third, I evaluate the global effects of local standards and find that European funds react to the American ASC 820 standard, long before the European equivalent of this standard, IFRS13 becomes effective. Even the European funds belonging to fund firms with no organic connection to the United States significantly improve valuations after ASC 820. This finding is consistent with the "Peer Pressure" literature which shows that the quality of voluntary disclosures is positively affected by the disclosure quality of the peers.

Finally, I evaluate the effects of activist institutional investors on fund valuation accuracy. Within a propensity score matching framework, I find evidence that funds that receive investments from large public pension funds have significantly better valuations before fair value measurement. However, this difference is eliminated after the introduction of ASC 820, showing that fair value measurement not only improved overall valuation accuracy but also contributed to the standardization of higher-quality valuation.

Overall, this study shows that fair value measurement creates added value, even for the private equity market in which the investment valuations depend strictly on personal judgements, instead of structured market quotations. This result is significant because it asserts that fair value measurement is a significant step towards alleviating, at least some of the agency problems in the private equity industry, resulting from low-quality interim reporting. This positive effect would contribute to the decisions of investors on their portfolio allocations and would help them to assess the role private equity investments should play for those portfolios better.

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