In Pursuit Of Information: Information Asymmetry in Private Equity Commitments

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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.

JEL Classification: G11, G23, G24
Keywords: Information Asymmetry, Fund Selection, Investment Consultants, Institutional Investors, Public Pension Funds, Private Equity, Herd Behaviour

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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, Liechtenstein, 2011; Azzi, 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, Rauh, 2013; Morkoetter, Schori, 2021) by discussing the effects of the board of trustee composition on investment processes and fund selection performance.

2 Background & Literature Review

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: Private Equity Fund Strategy Breakdown per Vintage]

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.

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 2: Private Equity Commitments of 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 3: US Public Pension Fund Ownership of Private Equity 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 nonperformance factors (e.g. decision-making capability, consistent investment philosophy, the effectiveness of presentations) affect consultant recommendations, but they do not find an overperformance for these recommendations.

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, they 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 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.

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. Overall, academic literature supports the hypothesis that institutional investors use peers' investments as information sources.

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.

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 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.

[Table 1: Descriptive Statistics]

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.

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:

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

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.

[Table 2: Consultant-Driven Deals]

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

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

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.

[Table 3: Consultant Contribution to Fund Selection]

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 3 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.

[Table 4: Contribution by Consultant Type]

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:

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

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

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

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.

[Table 5: Fund Selection Practices of Specialist Consultants]

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 management 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%.

[Table 6: Trustee Experience & Reliance on Consultants]

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 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.

[Table 7: Trustee Experience & Fund Selection Performance]

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.

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 8: Pension Fund Herding - Pre/Post Commitment]

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 these robustness tests.

[Table 9: Pension Fund Herding - Robustness]

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.

[Table 10: Herding Triggers - PPF Size]

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.

[Table 11: Herding Triggers - PPF Experience]

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.

[Table 12: Herding Triggers - Strategy Riskiness]

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.

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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Figure 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.

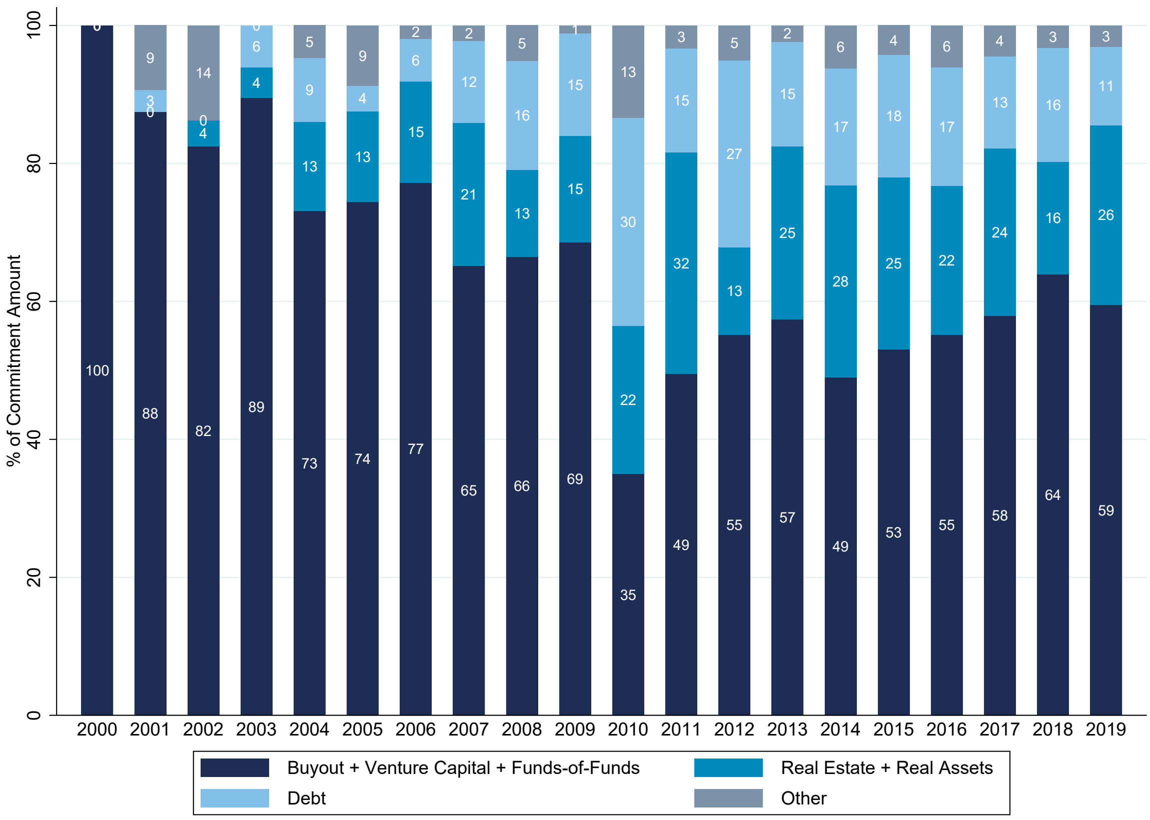

Figure 2: Private Equity Commitments of Public Pension Funds

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

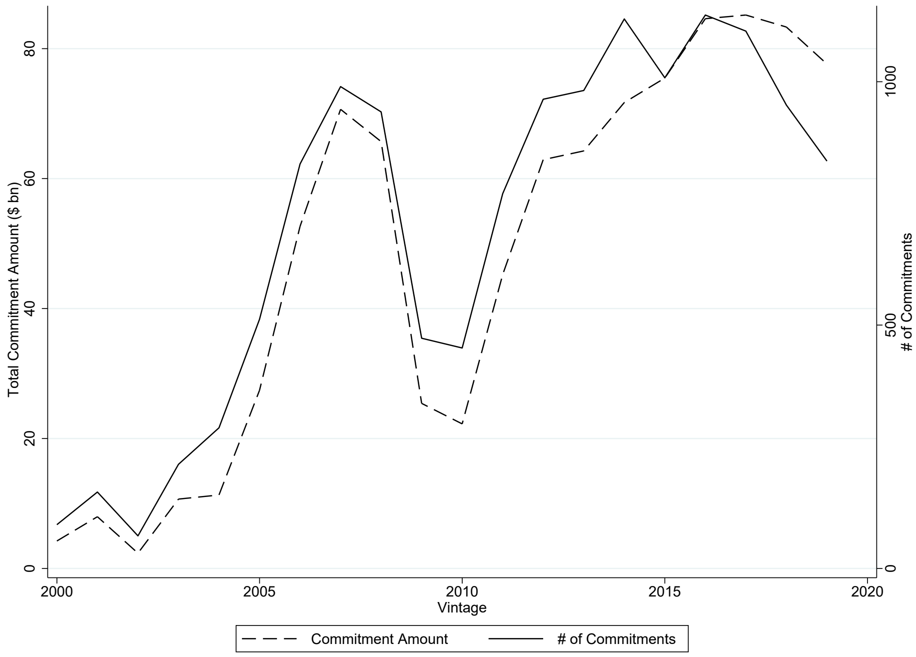

Figure 3: US Public Pension Fund Ownership of Private Equity Funds

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

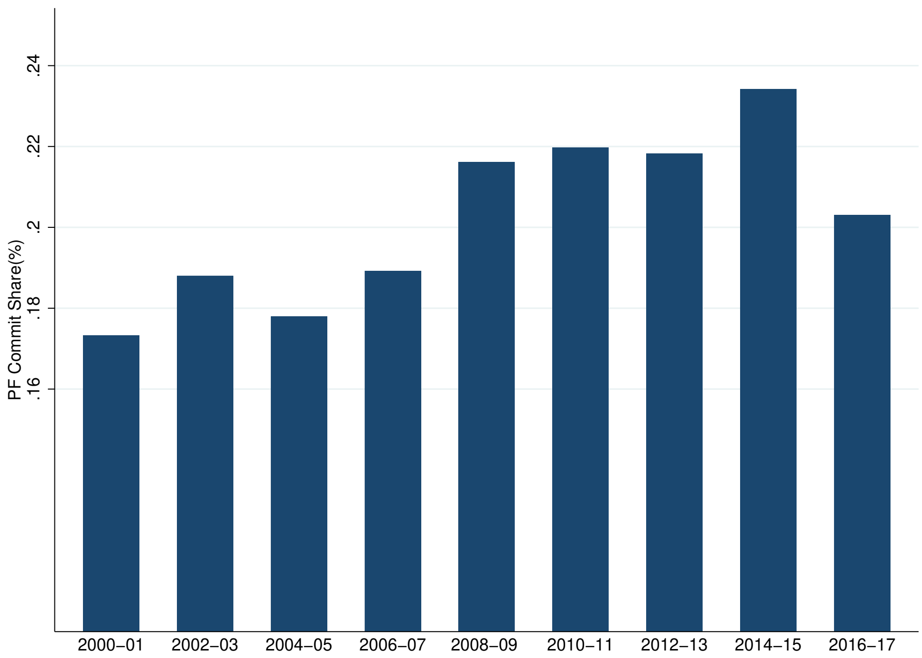

Table 1: Descriptive Statistics

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.

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 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.

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 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.

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 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.

	(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 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.

	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 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.

	(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 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.

	Consultant-Driven Selections			Internally-Driven Selections		
Fund IRR	(1)	(2)	(3)	(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 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.

	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 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 %	(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 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.

	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 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.

	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 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.

	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