

Herd Behaviour of Institutional Investors: Evidence from Private Equity Investments of Public Pension Funds

Onur Sefiloglu *

Cass Business School, City, University of London

Abstract

Public pension funds exhibit herd behaviour in their private equity fund commitments. An increase of 10 pp. in the ownership of a private equity fund by peers results in a 2.8-3.6% increase in commitments by public pension funds. Herd behaviour intensifies when the availability of high-quality information is limited, such as highly volatile or down markets, and for riskier businesses with higher uncertainty about the investment outcome. Moreover, reputational and career-related concerns also trigger herd behaviour. Public pension funds herd towards similarly-sized peers against which their investment performance is compared. Herding significantly increases within the state, and the investments made following same-state peers underperform.

JEL Classification: G11, G23, G24

Keywords: Institutional Investors, Public Pension Funds, Private Equity, Herd Behaviour

*I am very grateful for the comments of Francesc Rodriguez-Tous and Paolo Volpin. Address: Cass Business School, City, University of London, 106 Bunhill Row, London EC1Y 8TZ Email: onur.sefiloglu@cass.city.ac.uk

1 Introduction

An investor's investment decision can be considered herding if she would not have made it without knowing what other investors do, but invests when she finds out others also do it (Bikhchandani and Sharma, 2000). A vast empirical literature evaluates institutional investors' herd behaviour in the traditional financial markets, such as public equity and bonds. Nevertheless, although the popularity of private equity investments has been booming among institutional investors during the last two decades, academics neglected the influence institutional investors have on each other while deciding on their private equity investments.

This paper aims to fill this gap in the academic literature by analyzing the herding of public pension funds ("PPF") in their private equity ("PE") commitments, following the theoretical literature on herd behaviour in financial markets. One important challenge is how to measure herding for this illiquid asset class. Lakonishok, Shleifer, Vishny (1992) measures herding in the stock market as the investors' tendency to buy or sell particular stocks at the same time. 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 for the fund's life, which is normally ten years. Moreover, a particular PE fund has only a few dozen investors on average, a figure dramatically low compared to public equities and bonds. Considering these major differences, this paper measures herding in PE fund commitments as the influence of other PPFs' commitments in a specific PE fund on the commitment amount of a PPF.

The first result of the paper is that PPFs herd, i.e. they are influenced by the investment decisions of other PPFs while deciding the amount of commitment to make to a specific PE fund. A 10 pp increase in PPF ownership results in an increase of 2.8-3.6% in the amount committed.

In the next step, I investigate the motivations of the observed herd behaviour. As summarized by Graham (1999), the theoretical literature on herding behaviour discusses the motivations for herding in 3 groups: (1) Informational Herding (2) Reputational Herding (3) Investigative Herding. This paper focuses on the first two groups. Under the informational herding hypothesis, investors copy others' actions either because they believe the inferred information is superior or because they are unable to obtain high-quality information. The results of the tests on the informational herding hypothesis can be summarized in three steps. First, herding behaviour intensifies during down markets, and this result is in line with Chang, Cheng, Khorana (2000) and Popescu and Xu (2014, 2018). Second, herding is much stronger during high market volatility. This finding

contradicts Christie and Huang (1995) and Hwang and Salmon (2004), which find that uncertainty does not have a significant effect on the herding but is in line with Bekiros et al. (2017), Economou et al. (2018) and Duygun et al. (2021) that document a positive relationship between uncertainty and herd behaviour. Finally, herd behaviour is higher for riskier private equity strategies with limited information availability, which is in line with Raddatz and Schmukler (2013) which arrive at a similar conclusion for the pension fund investments in traditional asset classes, and Cai et al. (2019) for investments in corporate bonds. Overall, the results obtained support the informational herding hypothesis, which can be interpreted that PPFs try to alleviate their informational problems that surge during increased uncertainty and for businesses with limited available information by following the actions of other PPFs.

The second theoretical motivation of herd behaviour assessed in this paper is the reputational herding hypothesis. Under this hypothesis, agents herd either to avoid losing their reputation as a result of an “unconventional failure” which will create the perception that they are low quality, or with career concerns stemming from the fact that performance is compared relative to benchmarks and low performance have severe consequences such as losing jobs. Additionally, politically-affiliated PPF trustees have incentives to herd to not underperform against peers and hurt a future political career. Following Blake and Timmermann (2002), which discuss that PPF performances are evaluated compared to benchmarks built from similarly sized funds, I evaluate the reputational herding hypothesis in size subgroups. First, I find that all size groups herd, and they herd towards similarly-sized institutions. This result provides support for the reputational herding hypothesis and is in accordance with the findings of Sias (2004), Popescu and Xu (2014) and Blake et al. (2017), which show that institutional institutions herd in subgroups.

To assess the reputational herding hypothesis from a different angle, I build on the findings of Hochberg and Rauh (2013) and Bradley et al. (2016), which show that political aspirations of pension fund trustees lead them to overweight investments to local funds, stocks and politically connected companies, and I evaluate the in-state herd behaviour. I find that public pension funds herd towards their in-state peers, and this herd behaviour is directed towards the ones that are similar to them in terms of size. Overall, the obtained results provide significant support for the reputational herding hypothesis.

In the last part of the paper, I evaluate the consequences of herd behaviour. PPFs benefit from following other PPFs, but they perform much worse when they follow their in-state peers. This finding signals that following same-state funds in investments have motivations other than obtaining high returns, and in line with Andonov et al. (2018), political aspirations hurt the performance of public pension fund investments in private equity.

This study uses the PPF industry of the United States as its laboratory. Freedom of

Information Act (“FOIA”) necessitates transparency in the disclosures for the PPFs in the United States, and they are obliged to disclose the details of their commitments to private equity funds in their Comprehensive Annual Financial Reports (“CAFR”). PE fund commitment data of PPFs is obtained from Bloomberg Professional terminal, which compiles this information directly from the CAFRs of the PPFs. The working sample accommodates close to 15,000 commitment observations from 223 public pension funds, in 9 different private equity fund strategies, between private equity fund vintage years of 1992 and 2020. The sample size is comparable to the previous research using similar data (Hochberg and Rauh, 2013; Andonov et al., 2018).

This paper contributes to three strands of academic literature. First, in my knowledge, it is the first paper documenting herd behaviour in the private equity industry; thus, it contributes to the empirical literature on herd behaviour in financial markets. (Lakonishok, Shleifer, Vishny, 1992; Christie, Huang, 1995; Wermers, 1999; Sias, 2004; Blake, Sarno, Zinna, 2017). The paper provides insights on the herd behaviour for a new asset class, with a new methodology that assesses the influence of peers’ actions on investment decisions.

Moreover, this paper contributes to the literature on the private equity investments of institutional investors (Gompers and Lerner, 1996; Lerner, Schoar and Wongsunwai, 2007; Sensoy, Wang and Weisbach, 2014) by extending our knowledge on the private equity investment practices of a specific type of institutional investor, public pension funds.

Finally, the paper contributes to the literature on the governance of public pension funds (Novy-Marx and Rauh, 2011; Andonov, Bauer, Cremers 2012, 2017) and the local bias in their investments (Brown, Pollet and Weisbenner, 2009; Hochberg and Rauh, 2013) by deepening our understanding on the effects of political affiliations on governance practices and investment decisions.

The paper proceeds as follows: Section 2 lays out the background and reviews the related literature. Section 3 defines the empirical methodology and introduces the data. Section 4 presents and discusses the empirical results. Section 5 concludes.

2 Background

2.1 Private Equity Industry

A PE fund is a partnership of fund investors (limited partners), which are mostly large institutions (e.g. pension funds, university endowments, banks, insurance companies), and fund managers (general partners) 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 dissolves after all of the fund’s investments are liquidated and proceeds are distributed back to the investors.

Unlike other traditional asset classes like public equities and bonds, which provide ample liquidity to the investors, PE is a very illiquid asset class. For example, for the buyout funds, the commitments to the PE funds are used to acquire private companies, and these companies are held by the funds for four years on average before being sold and sales proceeds are distributed back to investors. During this period, the investors have no say in the fund’s investment decisions, and under normal circumstances, they cannot have their money back earlier (unless they sell their ownership in the secondary market, which is also illiquid).

Despite its challenges, PE has been wildly popular among institutional investors during the last couple of decades. PE fundraising increased by ten-folds from \$110bn to \$1.1trn, from 2003 to 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 Buyout funds, in its larger definition, there are several different fund strategies classified as private equity. Among these strategies, “Buyout” funds invest in mature private companies with room for improvement in operational and financial efficiency. “Venture Capital” and “Growth” funds provide capital to start-ups and early-stage companies with high potential, but also with a high risk of failure. “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. Small institutional investors that do not have direct access to reputable PE funds invest in them through “Funds-of-Funds”, which specialize in choosing PE funds, and building a portfolio of them.

2.2 Herd Behaviour in Financial Markets

2.2.1 Theories of Herd Behaviour

There is a vast academic literature evaluating herd behaviour in financial markets, mainly by focusing on the investing activity in the traditional markets such as equities and bonds and equity analysts’ forecasts. Using the classification of Graham (1999), theoretical

motivations of the herd behaviour can be grouped into three categories: (1) Informational herding, (2) Reputational herding, (3) Investigative herding.

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). Reputational herding occurs due to the agent's career concerns, especially when her performance is assessed relative to benchmarks/peer performances (Scharfstein and Stein, 1990; Trueman, 1994; Zwiebel, 1995). Short-term focused agents engage in investigative herding by following the actions of the early traders, especially when the early-obtained information is useless unless many other agents possess it (Brennan, 1990; Froot, Scharfstein, Stein, 1992; Hirshleifer, Subrahmanyam, Titman, 1994).

This paper focuses on informational and reputational explanations for the herding behaviour and leaves the investigative herding out. This type of herding necessitates an actively traded and valued market in which traders benefit from their private information being shared by others. PE investments do not provide such a trading and profit opportunity; therefore, investigative herding motive is not considered within this paper's scope.

2.2.2 Reputational Herding

The effects of career concern on herd behaviour are deeply evaluated by the academic literature, especially for the mutual and hedge funds and equity analysts' recommendations. Morck, Shleifer, Vishny (1989) state that company boards evaluate performance relative to the other firms in the same industry, and they are less eager to punish managers for underperformance if the whole industry is suffering. Similarly, Scharfstein and Stein (1990) discuss that herd behaviour can arise due to managers' attempts to enhance their reputation as decision-makers since a bad investment decision will be less criticised if it is similar to the decisions of other colleagues. They show that herding is more likely when the managers' outside options are unattractive, and the compensation depends on relative performance. Trueman (1994) evaluates the herding behaviour of equity analysts and show that they herd by following the analyst recommendations released before theirs, and this action positively affects the investors' perception of the analysts' forecasting ability. Graham (1999) discusses that analysts with high reputation herd to protect their current status and compensation. Chevalier and Ellison (1999) and Avery and Chevalier (1999) show that termination is more performance-sensitive for young fund managers, which creates an incentive for them to decrease unsystematic risk and herd into more conventional portfolios. Dasgupta and Prat (2008) discuss that for the career-concerned asset traders, taking contrarian positions is reputationally costly since if the trade turns unsuccessful, the trader will be singled out as being incompetent, and this leads to a

more conformist behaviour. Popescu and Xu (2014) discuss that institutional investors follow similar-type institutions, a conclusion that is also reached by Sias (2004).

Another strand of literature evaluates herding for pension funds. Blake et al. (2002) find that the performance of pension funds clusters around the median fund manager's performance, which is a sign of herding. The paper discusses that this result is because the survival of the mandated asset managers depends on their relative performance against their peer groups, which creates an incentive for them to herd. Blake et al. (2017) differ from the two papers above in the sense that it focuses on the herding in the asset allocation decisions, meaning that it elaborates the agency conflicts between pension fund stakeholders and the board of trustees. The paper shows that pension funds herd in their asset allocation decisions, and they tend to herd towards other similar funds (in terms of fund size and sponsor type).

2.2.3 Informational Herding

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 by the 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 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 riskier assets and for which the pension funds have 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, when the market uncertainty increases and the 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.

2.3 Public Pension Fund Governance and Incentives for Herding Behaviour

PPFs are administered by the central or state governments 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 the 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 located in the United States control assets amounting to \$4.8 trillion (National Association of State Retirement Administrators, 2021a). Since the interest rates are 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).

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. Together with the help of the professional investment staff, 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).

Trustees of PPFs are selected in 3 ways. “Elected” members represent the plan participants. “Ex-Officio” members act as the plan trustees by virtue of holding a public office. “Appointed” members are chosen by an elected official or a governing body. Ex-officio and appointed trustees are politically-affiliated, and according to Hess (2005), they represent 60% of the total PPF trustees.

Career concerns of the politically-affiliated trustees of public pension funds create incentives for them to act in self-interest. As Musalem and Palacios (2004, p.69) put it, a future political career exists as an external labour market for the politically-affiliated trustees. Plus, since the punishment for poor performance may be much more severe compared to the rewards obtained after a good performance, if a trustee is politically affiliated and has prospects of a political career, she has incentives to avoid negative publicity, which creates an incentive for them to herd towards benchmarks. Previous research shows that political aspirations affect the investment decisions of the politically-affiliated trustees. Hochberg and Rauh (2013) show that PPFs over-allocate assets to local investments. The overallocation is higher in states with more political misconduct, supporting the hypothesis that the overallocation may result from political pressures or ambitions. Relatedly, Bradley et al. (2016) find that PPFs overweight investments to stocks of local and politically connected companies, and this bias is positively related to the percentage of politically-affiliated trustees in the board. Andonov et al. (2018) show that the share of state officials in public pension boards is negatively related to the performance of private equity investments, mainly due to pursuing political benefit by shifting investments that contribute to economic development.

Another aspect that creates a herding incentive for the PPFs is the inadequate incentives to seek outperformance for the PPF investment teams. As Lerner et al. (2007) put it, PPFs provide inappropriate incentives, limited compensation and autonomy for the investment officers. Despite being huge financial institutions with enormous market power, the compensation of the investment teams is not comparable to that of private institutional investors. The funding deficits of PPFs are eventually compensated by the taxpayers, making it very difficult to justify paying the PPF staff according to the market realities. The criticisms made to Texas TRS, one of the large PPFs that uses a performance-based compensation scheme, by the public is a solid example which is summarized in the title of Miller (2017): “Teacher retirement system awash in bonus cash — yet still seeks help to fund health care”. Relatedly, Dyck et al. (2018) discuss that the possibility of a public outrage negatively affects PPF management teams’ willingness to offer competitive compensation packages to investment professionals, which leads to

hiring low-skilled investment personnel. Given that the overperformance is not awarded, but underperformance results in job risk, PPF investment teams have strong incentives to herd towards their benchmarks.

3 Data and Methodology

3.1 Measurement of Herding in Private Equity Commitments

3.1.1 Herding in Private Equity Fund Commitments

Assessing herd behaviour in private equity commitments is dramatically different from traditional investment classes such as equities or bonds. For the traditional investment types, depending on the type of the mandate (active/passive investing), there is continuous trading/rebalancing in the financial markets. So although there is a targeted allocation to these asset classes, investments within these classes continuously change, and the herding behaviour by the asset managers can be evaluated by tracking the correlation of the direction of their trades with the trades of other institutional investors. For example, one of the earliest and widely used measure for herding introduced by Lakonishok, Shleifer and Vishny (1992) defines herding as the tendency of money managers to buy (or sell) the same stocks at the same time.

In private equity commitments, however, there is no trading activity. Private equity investors define a target allocation to private equity investments, and each year they perform commitments to varying numbers of new private equity funds that start their fundraising process. The investment process ends for the investors once the commitments are made, and the remaining part of the private equity fund life is managed by the fund managers (general partners) until they fully liquidate the investments and distribute the proceeds back to investors. Therefore, the definition of herding in the context of private equity commitments will necessarily be different.

This paper defines the herd behaviour of public pension funds in their private equity investments as the level of influence the commitments of other PPFs have on the commitment decisions of the PPF of interest. A reasonable method to assess this influence would have been evaluating the effect of the existence of other PPFs as investors in a specific private equity fund on the binary decision of a PPF to commit in the same PE fund. However, this method is not feasible since our database only includes the commitments made, and it is not feasible to guess the other plausible commitment alternatives that each pension fund decided to stay away from. Therefore this paper takes advantage of another plausible alternative, which investigates how the commitment amount in a PE fund by a public pension fund is affected by the total commitments of the other public pension funds. It is important to note that capturing the herd behaviour by evaluating the commitment amount is much harder since PPFs might still herd by preferring

to commit in PE funds with larger PPF involvement, but this behaviour might not be reflected in the amount that they commit.

For PPF p , general partner g , PE fund i , commitment year t and private equity fund strategy s , this study is built on the following model and its extensions:

$$\ln \text{CommitRatio}_{p,g,i,t,s} = \alpha + \beta \text{PFCommitShare}_{p,g,i,t,s} + \gamma X_{g,i} + \theta_p + \mu_t + \nu_s + \epsilon_{p,g,i,t,s} \quad (1)$$

The variable, “CommitRatio”, is calculated by dividing the commitment amount by pension fund p in a specific private equity fund i to the average commitment pension p has made during the three years covering one year before and after the related commitment. So if a commitment is made in 2007, CommitRatio will compare the amount committed to the average commitment made by the PPF in private equity funds between 2006 and 2008. The reason to define a 3-years period instead of the single year in which the commitment made is the fact that the count of commitments per year is small for a majority of the pension funds, so comparing the commitment amount to the average commitment in a single year would be uninformative for these cases. It is important to note that using the alternative methods in which only the commitment year is considered or the absolute commitment amount is used instead of the CommitRatio metric provides similar results. “CommitRatio” variable has the advantages of being standardized and stationary, which eliminates distortions due to timing differences, and is comparably distributed among different subgroups of the working sample. The log-transformation of CommitRatio is defined as the dependent variable.

The independent variable of interest is “PFCommitShare”, which is calculated by dividing the total commitments made to the private equity fund i by all PPFs other than the fund of interest, p , to the fund size. So this ratio is the ownership ratio of all other PPFs in a given private equity fund. Using this variable, I aim to assess how the pension funds shape their commitment decisions based on the other pension funds’ collective actions.

A possible concern for the identification strategy is the existence of possible confounding factors. For example, one might argue that all pension funds might be pursuing funds with certain characteristics (e.g. past performance, the talent of the fund manager), and this might create an upward bias in the β coefficient we obtain. Defining “PFCommitShare” as the main independent variable is advantageous regarding the identification strategy since it naturally alleviates some of these concerns. This variable is the ownership share of one type of institutional investors, PPFs, meaning that residual ownership belongs to other types of institutional investors such as private pension funds, endowments, banks and insurance companies. Making the logical assumption that all of these institutions have the same motivation of having higher returns for their investments, factors such as past performance of the GPs’ funds and GP talent are hard to confound

the results. Other types of institutional investors would have similar incentives, which would make it difficult for pension funds to own a greater share of funds with certain characteristics structurally.

Matrix X in Equation (1) represents the additional control variables. Variables θ , μ and ν correspond to Limited Partner, Year, and PE Fund Strategy fixed effects. For all specifications in every test, standard errors are clustered at the Pension Fund level.

3.1.2 Herding in Private Equity Strategy Commitments

Another plausible method is to move one step up and evaluate the commitment decisions at the PE fund strategy-level since the PPFs might be re-shaping their allocations within PE strategy alternatives based on the allocations of other PPFs. For this evaluation, I combine each pension fund’s PE fund commitments under relevant PE fund strategy categories. One challenge is to decide how to treat fund-of-funds, since although this category is classified as a distinct strategy, in reality, these funds are tools for the smaller institutional investors to be able to invest in private equity funds that have one of the other eight strategies. Treating fund-of-funds as a distinct strategy for this test may bias the results since a small fund that observes a heavy move towards buyout investments by other PPFs may increase investments to fund-of-funds, but treating funds-of-funds as a distinct strategy may lead us to wrong conclusions. Therefore, taking into account the information provided by Prequin (2012) that funds-of-funds invest close to 60% of the commitments they collected to buyout funds, only for this test I make a simplifying assumption that funds-of-funds are buyout funds. Although this assumption is necessary for the consistency of this analysis, it by no means affect the regression results significantly.

To evaluate the strategy herding of PPFs in their private equity investments, I build the following model:

$$\ln StrategyShareRatio_{p,g,i,t,s} = \alpha + \beta PFCCommitShareStrategy_{p,g,i,t,s} + \theta_p + \mu_t + \nu_s + \epsilon_{p,g,i,t,s} \quad (2)$$

In Equation (2), the independent variable, “StrategyShareRatio”, is the commitment share of PPF p, in vintage year t, of strategy s, divided by the total size share of all funds with vintage t and strategy s among all funds with the same vintage. For example, if PPF p committed 50% of its PE allocation to buyout funds for the vintage year 2011, and the buyout funds represent 25% of the PE fund universe in terms of total fund size for the same vintage, StrategyShareRatio will be calculated as 2 (50%/25%), which will mean that compared to the total fund universe, PPF p invested heavily on buyout funds for 2011 vintage. To normalize the distribution and neutralize the effect of outliers, I work with the logarithmic transformation of the independent variable.

The independent variable “PFCCommitShareStrategy” measures the total ownership of all PPFs except the one of interest in a specific PE strategy and a specific vintage.

Similar to the variable “PFCommitShare” which was introduced in Equation (1), this variable is calculated by dividing the total commitments to PE strategy s , in vintage year t , by all PPFs except p , to the total size of all funds with PE strategy s and vintage year t .

The model introduced above aims to uncover the effect of a disproportional shift in the PE strategy allocation by all PPFs (excluding the one of interest) in the PE strategy allocation of individual PPFs. The model also includes the variables θ , μ and ν , which correspond to Limited Partner, Year and PE Fund Strategy fixed effects.

3.2 Data and Descriptive Statistics

According to the Freedom of Information Act, PPFs are required to provide detailed information on their investment activity in their CAFRs. The data provided includes details about the private equity commitments, including the commitment year, commitment amount, PE fund name and GP name. The dataset used in this study is obtained from the Bloomberg Professional terminal, which obtains the commitment details directly from the CAFRs of PPFs. The complete dataset, which was collected as of July 2020, includes 22,816 commitment observations by 365 PPFs, in 6,130 distinct private equity funds managed by 1,767 general partners.

To obtain the working sample, some necessary data filtering was made. Firstly, 5,970 observations with missing crucial information (commitment amount, private equity fund size, general partner information, limited partner information) are eliminated. 136 observations are dropped because they are old (before 1987), or they have very small commitment (below \$ 1mn) or PE fund size (below \$ 10mn). 252 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 which has a completely different nature of operation. 1,736 observations for private equity funds in which there is only one pension fund as an investor or a single pension fund owns the majority of the private equity fund (over 75%) are left out. Finally, 184 observations belonging to private equity funds with inconsistency between the fund size and the total collected commitments are dropped. Following these data filtering, the working sample with 14,538 commitment observations by 223 public pension funds is obtained, which spans the period between 1992 and 2020.

The final sample corresponds to a total US PPF commitment of \$980 bn. 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. According to Preqin (2019), total fundraising by private equity funds between 2000 to 2019 amounts to \$6.5 trn globally. The working sample contains private equity funds with a total size of \$4.8 trn for the vintages of the same period, corresponding to 73%

of private equity funds in terms of size. Moreover, the sample highlights ownership of 20% of all the private equity funds by the public pension funds located in the US. Given that all public pension funds account for close to 30% of the private equity fundraising (Meerkaat and Liechenstein, 2009; Comtois, 2019) and US pension funds own close to 60% of pension fund assets globally (OECD, 2020), we can conclude that the sample is highly representative of the total US PPF investment activity in PE funds.

Table (1) describes the data. Panel (A) presents the summary statistics for the commitment amounts of PPFs in PE funds. The upper block of Panel (A) provides a breakdown for varying PE fund strategies. 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 very large commitments to mega-funds. The lower block of Panel (A) provides the breakdown of commitments for pension fund size categories, with 1 being the smallest and 5 the largest. Average commitments to private equity increases from \$17.4 mn to \$154.5 mn from the smallest to the largest PPF group.

Panel (B) of Table (1) provides the summary statistics for the main dependant variable used throughout the study. This variable, “lnCommitRatio”, which was introduced in the previous section, standardizes the commitment amount such that the variable has very similar distributions among different subgroups, as we can observe in Panel (B). The variable is stationary with distributions close to normal and with similar dispersions for all subgroups, which would alleviate some potential identification issues and let us perform reliable comparisons among the subgroups.

Panel (C) clarifies the differences among PPF asset subgroups. Smallest (largest) PPF has an AUM of \$36 mn (\$386 bn). Higher size categories accommodate smaller numbers of PPFs since these PPFs are much more involved in PE investments. PPFs in category 1 have commitments in 20 PE funds on average, whereas this number increases to 308 for category 5. For some of the analysis, I use a broader categorization for PPF size, in which the size categories 1, 2 and 3 (4 and 5) are grouped as “Small” (“Large”).

Panel (D) presents the other variables used in the analysis. “Net IRR” is the dominant performance metric for private equity funds, calculated based on the cash flows generated by the fund as a whole. Given that private equity fund investments have no active market valuations, IRRs are calculated by the private equity fund managers based on their subjective valuations throughout the fund’s life. Only when the fund liquidates its last investment and distributes the proceeds to its investors, the IRR of the fund is finalized. Therefore I limit my analysis on performance for fund vintages before 2011, for which we can be sure that the fund performance is either definite or close to being so. It is important to note that specifying later cut-off years do not change the obtained results materially. The mean IRR of 9.4% is comparable to the figures presented by the previous research on private equity fund performance (Sensoy, Wang and Weisbach, 2014;

Robinson and Sensoy, 2016).

“PFCommitShare” variable measures the total ownership share of other PPFs, and it is the main explanatory variable of this analysis. “SameStateCommitShare” makes the same calculation by only taking into consideration the other pension funds located in the state of the PPF of interest. As the median value of 0 suggests, for the majority of the observations, another same-state fund does not accompany the investment in a private equity fund. The last two variables, “lnGPFundTotalSize” and “GPExperienceYear” are used to control for GP characteristics. “lnGPFundTotalSize” is the log-transformation of the total private equity fund sizes managed by a GP, built as a proxy for the GP size and reputation, and “GPExperienceYear” is the difference between the observation year and the year the GP started its first private equity fund, standardized for each year.

[Table 1: Descriptive Statistics]

4 Empirical Results

4.1 Do Public Pension Funds Herd?

Table (2) presents the regression results based on the model introduced by Equation (1). For all model specifications, the dependent variable is lnCommitRatio, and the independent variable of interest is PFCommitShare.

The size of the private equity fund may be a confounding factor if PPFs tend to invest more in a specific size group than other types of investors. This possible confounding effect is controlled by the inclusion of the variable “lnFundSize”, which is the natural logarithm of the size of the committed PE fund. General partner characteristics are also considered. PPFs may be more inclined towards investing more in the PE funds of larger PE houses with higher reputation or more expertise in private equity. “lnGPFundTotalSize” is the natural logarithm of the total size of all PE funds managed by each GP, which is used as a proxy for GP reputation and size. “GPExperienceYear” is the difference between the commitment year and the year in which the GP introduced her first PE fund, standardized by demeaning and dividing to yearly standard deviations. This variable captures the heterogeneity in GP experience in private equity investments. The specifications also introduce fixed effects to control for pension fund, commitment year and PE fund strategy-specific characteristics.

In Table (2), we observe a statistically significant coefficient for the variable “PFCommitShare”, which is highly robust to the inclusion of control variables and fixed effects. These results suggest that for a PE fund with 10 pp. higher PPF ownership, investment of a PPF in increases by 2.8-3.6% compared to the average amount invested in private equity funds. For the mean commitment of \$68 million, this corresponds to an increase of \$2 million.

[Table 2: Pension Fund Herding in Private Equity Fund Commitments]

Table (3) evaluates the herd behaviour of PPFs focusing on their PE strategy commitments, based on the regression model introduced by Equation (2). The models include the dependent variable “lnStrategyShareRatio”, independent variable “PFCommitShareStrategy” and pension fund, vintage year and PE strategy fixed-effects. The data is at PPF x PE Strategy x Vintage Year level, meaning that commitments to separate PE funds with the same PE strategy and the vintage year are combined for each PPF.

Different specifications in Table (3) highlight a robust and significant relationship between PFCommitShareStrategy and lnStrategyShareRatio, even with the complete set of fixed effects in place. The coefficients suggest that 10 pp. increase in the ownership share of all other PPFs in a given PE strategy results in a 15-24% increase in the ratio of strategy allocation of a given fund to the strategy allocation of all PE funds.

Results presented by Table (2) and Table (3) underlines similar conclusions. PPFs are influenced by the strategy allocation and fund commitment decisions of other public pension funds.

[Table 3: Pension Fund Herding in Private Equity Strategy Commitments]

4.2 Why Do Public Pension Funds Herd?

The next step is to evaluate the reasons for herding by PPFs, in the light of theoretical motivations of the herd behaviour. However, it is crucial to note that there is a very significant difference in the incentive mechanisms for PPFs when it comes to the evaluation of PE fund commitments compared to the investments in traditional securities. Previous research heavily focuses on the herd behaviour of PPFs in public equity and bond investments. For these traditional investment types, pension fund management (board of trustees and the investment team) determines the yearly allocations and gives mandate to fund managers with specific investment budgets. It is the fund manager who determines which specific securities to be invested in, and the herding decision that the literature evaluates is, therefore, the one of these fund managers.

For the PE commitments, the situation is different. After deciding on the budget allocation to private equity investments, pension fund management determines the private equity funds to be committed to and the amount of these commitments. Fund managers of these private equity funds mostly use the committed funds to partly/fully acquire private companies, in which the PE fund of interest is mostly the only shareholding PE fund; therefore, herding by the PE fund manager at the investment level is not a significant possibility. Consequently, evaluation of the herding behaviour of PPFs boils down to investigating the PE fund commitments of the PPF trustees and how these commitments are affected by the decisions of peers.

In this paper, I evaluate the reasons for the herd behaviour by testing four different hypotheses on the informational and reputational explanations. To assess the informational herding explanation, I first evaluate how the market conditions affect the commitment decisions of pension fund management. Then, I focus on individual PE fund strategies and find out how the varying riskiness and uncertainty among these strategies affect the herding behaviour.

For the reputational herding, I begin by testing whether pension funds herd towards similar funds. Furthermore, in the next step, I assess the herding at the state level to check whether the commitments of the same-state peers affect the decisions of the PPFs.

4.2.1 Informational Herding

4.2.1.1 Herding and Market Conditions

The quality of available information deteriorates during periods with unfavourable market conditions. Based on the information herding hypothesis, investors may be more inclined to omit their own ideas and beliefs and be more affected by the investment decisions of others when the financial markets are volatile and investor sentiment is negative.

Hypothesis 1: Herding behaviour intensifies when the market conditions deteriorate.

To evaluate the hypothesis above, I extend the model introduced in Equation (1) by interacting the “PFCommitShare” variable with commitment year dummies to observe how the herding coefficient evolves in time. The results are presented in Figure (1). Along with the yearly coefficients, the figure also includes the 95% confidence intervals calculated based on the standard errors clustered at the pension fund level. Years before 2000 was omitted in Figure (1) because of the very limited number of observations. Figure (1) provides several key observations that deserve discussion. To begin with, with the exception of two years, we observe a positive herding coefficient for every year. Moreover, although statistical precision decreases due to the separate evaluation of herding behaviour for years and the limited number of observations for older periods, more than half of the year coefficients have statistical significance. Finally, and most importantly, the coefficient shoots up at three different time periods, 2000, 2007-2008 and 2020, which correspond to the periods of financial crises and high market volatility. We also observe a significant contraction in the coefficient in the years when markets rebound. Overall, the information provided by Figure (1) strengthens the argument on the existence of herding in private equity commitment and supports the Hypothesis 1 which claims that deteriorating information quality would trigger the intensity of the herding behaviour.

[Figure 1: Public Pension Fund Herding by Commitment Years]

To systematically test the observations made using Figure (1), I use two sets of market

data that would be informative about the market sentiment and the level of uncertainty in the financial markets: (1) Changes in S&P 500 Index (2) VIX Index. The dataset only provides the commitment year for the observations; therefore, for each observation, I calculate the variable "SP500Change" as the percentage change in the index between the first and last working day of the commitment year. For the VIX index, I calculate the variable "AvgVIX" as the average of daily observations of the VIX index for the commitment year for each observation. Both of these variables are imprecise measures for market conditions because of the inability to pinpoint the specific commitment days/months, but it would be fair to assume that the measurement error will be random for the observations and, therefore, will not result in a bias in the coefficients of interest.

To check how the herding coefficient is affected based on the market sentiment, I begin with Equation (1) and interact the "PFCommitShare" variable by the two sets of market variables introduced above, also including the level terms of these variables into the regression model. Results are presented separately in the two panels of Table (4). Panel (A) presents the results of the tests that evaluate the change in herding coefficient related to the change in S&P 500 Index. On top of the standard model introduced by Equation (1), the models in this table include the variable "SP500Change", and the interaction term "PFCommitShare x SP500Change" which will capture how correlated the level of herding is to the changes in S&P 500 Index. We observe negative and statistically significant coefficients for the interaction term, which suggest that herding behaviour intensifies during the years in which financial markets perform poorly. Panel (B) of Table (4) replicates the same analysis by evaluating the correlation of herding behaviour with the VIX index. The interaction coefficient is robustly and significantly positive, suggesting that the herd behaviour of PPFs soar during periods of high market volatility.

[Table 4: Public Pension Fund Herding vs Market Conditions]

The results of the tests discussed above are consistent, they are in line with the observations made based on Figure (1), and they support the hypothesis that market risk and uncertainty results in increased herd behaviour. PPF trustees have a greater tendency to become influenced by what other peers do under increased uncertainty. These results are consistent with the findings of Chang, Cheng and Khorana (2000) and Popescu and Xu (2014, 2018), which show that herding behaviour intensifies during down markets, and Bekiros et al. (2017), Economou et al. (2018) and Duygun et al. (2021) that document a positive effect of fear and uncertainty on herding.

4.2.1.2 Herding and Riskiness of the Private Equity Strategy

The second step to investigate the effect of uncertainty and risk on the herding behaviour of public pension funds is to evaluate the herding behaviour for different PE fund strategies. Different strategies have varying levels of riskiness related to the maturity of the invested company, the business and the type of investment. Prequin (2014) evaluates the riskiness levels of different PE fund strategies based on the standard deviation of their returns and points out that PE funds with Venture Capital (Including Early Stage) and Growth strategies possess the highest levels of riskiness. This is understandable since these funds invest in young companies with unproven potential and a significantly high risk of failure. These strategies are followed by Buyout funds, which invest in mature firms with solid histories, but boost risk (and expected returns) by relying heavily on leverage. Real Estate investments promise more reliable cash flows (rents), but since some very risky subcategories exist (i.e. “Opportunistic Real Estate”) that invest in very risky properties with little to no cash generation, the overall riskiness of the Real Estate strategy ends up to be very similar to Buyout funds. Real Assets funds invest in commodities, and infrastructure projects which promise steady and secure cash flows with low volatility, decreasing the riskiness significantly. Finally, although the riskiness of Debt investments differ based on the type of investment (direct lending, mezzanine, distressed debts), overall, debt is the private equity strategy with the lowest level of riskiness. If risk and uncertainty is a factor that affects the herd behaviour of PPFs, we would expect higher levels of herding for the commitments in PE funds with riskier strategies such as Venture Capital & Growth, Buyout or Real Estate, and we would expect the herd behaviour to be lower for Real Asset and Debt strategies.

Hypothesis 2: Herd behaviour intensifies for riskier PE strategies with lower information availability and higher uncertainty.

Table (5) presents the results of the regressions based on Equation (1), ran separately for the PE fund strategies discussed above. The coefficients obtained for separate private equity strategies are also presented in Figure (2) for a clearer demonstration. The results turn out to be completely in accord with the discussion made above, with the herding coefficient being highest for the riskiest strategies, VC & Growth, followed by Buyout and Real Estate strategies, and lowest (and statistically not significant) for Real Asset and Debt strategies. These results suggest that the herd behaviour of PPFs intensifies when they are investing in PE funds with riskier strategies, for which the availability of high-quality information is limited.

[Figure 2: Public Pension Fund Herding by Private Equity Strategy]

Panel (B) of Table (5) approaches the same question from a different, albeit familiar angle, by using Equation (2) to evaluate the strategy-level herding. Results are affirmative

of the ones presented in Panel (A), with the highest coefficients obtained for Growth & VC strategies, and the lowest ones are observed for Real Asset and Debt strategies.

[Table 5: Public Pension Fund Herding by Private Equity Strategy]

The results presented in Table (5) are consistent with the results obtained in the previous section. Similar to market risk and uncertainty, investment risk also triggers herding for PPFs. These results are in line with Raddatz and Schmukler (2013), which show that pension fund herding increases for riskier investments and for investments with low information availability. Overall, the results of the tests provide significant support for the information herding explanation.

4.2.2 Reputational Herding

4.2.2.1 Peer Herding

Previous research shows that career concerns are significant determinants of herd behaviour. The fact that performance evaluations are made relatively to benchmarks composed of similar institutions lead the agents to herd towards their own benchmarks, limiting the possibility of an “unconventional failure”. For the pension funds, Blake and Timmermann (2002) show that peer-group benchmarks are much more prevalent with the existence of separate return indices for small and large funds. Relatedly, Blake, Lehmann and Timmermann (2002) discuss the importance of these indices, given the fact that the survival of the fund managers managing the investments of pension funds depend on their success in comparison to peers, creating a significant incentive for herding. Blake, Sarno and Zinna (2017) confirm this finding for pension funds by showing that pension funds of similar types herd in subgroups based on funds size or sponsor type. If the pension fund trustees are also motivated by similar reputational considerations, we would expect herding behaviour about private equity fund commitments to intensify towards pension funds with similar sizes.

Hypothesis 3: Pension funds herd towards similarly-sized peers.

Table (6) presents the results of tests that evaluate herd behaviour for PPF size groups. The columns represent separate tests performed on five subgroups based on the total asset under management. The regressions are based on the main model introduced by Equation (1). The coefficient that measures the herding behaviour, “PFCommitShare”, is statistically significant for all size groups, with the significance and magnitude increasing for larger fund sizes, even though the coefficients for subgroups are not statistically significantly different from each other. These results seem to be in line with Graham

(1999), which shows that high reputation triggers herding behaviour with the intention to protect this reputation. However, while evaluating the herding behaviour for the size subgroups, we should not overlook the possibility of a reverse causality situation since higher coefficients for large PFs may be because of the fact that small PFs herd towards the commitment decisions of the large funds. To clarify this issue and check Hypothesis 3, I break down the variable “PFCommitShare” into two groups, “SmallPFCommitShare” and “LargePFCommitShare”. The small PF group is composed of the size groups 1, 2, and 3, and the large PF group is built up of groups 4 and 5.

[Table 6: Public Pension Fund Herding by Fund Size Categories]

The tests presented in Table (7) evaluate Hypothesis 3. The coefficients for “SmallPFCommitShare” and “LargePFCommitShare” inform us regarding the direction of herding for each size categories, and these coefficients are also presented in Figure (3) for an easier interpretation. The first important observation to be made is that small funds herd towards other small funds, but they do not herd towards the large funds. The differences for coefficients are statistically highly significant for size groups 1 and 2. Similarly, larger size groups herd towards large funds, with statistically significant coefficients for size groups 3, 4 and 5. We also observe that herding towards small (large) funds decrease (increase) monotonically with PF size. There are two important conclusions to be drawn from these results. First, the herding coefficients obtained for large funds are not a result of reverse causality since small funds do not herd toward the large funds. Large funds herd, and they herd towards their close competitors. Second, reputational concerns matter for PPFs. Their commitment decisions are influenced by the decisions made by similar pension funds. These results are in line with the findings of Sias (2004), Popescu and Xu (2014) and Blake, Sarno and Zinna (2017), and they constitute strong support for the reputational herding hypothesis.

[Figure 3: Herding by Fund Size]

[Table 7: Public Pension Fund Herding by Fund Size Categories - Herding Direction]

4.2.2.2 Same-State Herding

The final step in evaluating the reputational herding behaviour of public pension funds is to find out how the commitment decisions of PFs are affected by the actions of their same-state peers. As discussed above, PPF trustees with political career aspirations have incentives to “not underperform” against their same-state competitors since these defeats will be locally highlighted and have detrimental effects on the career prospects of the trustees. If these aspirations play a role in the decision making processes of the

trustees, we should be able to observe a herding behaviour towards the PE funds with heavy same-state PPF ownership.

Hypothesis 4: Pension funds herd towards same-state peers.

Table (8) presents the results. Herding towards same-state peers is captured by the variable “SameStateCommitShare” which is calculated as the total ownership percentage of all other same-state PFs in a PE fund. “SameStateCommitShare” is a subset of “PFCommitShare”, and including this variable to the model in Equation (1) can tell us if same-state involvement affects the commitment decisions. In Panel (A), Columns 1 to 5 perform typical tests with reduced/extended models, and we observe a statistically highly significant and robust effect of same-state ownership. What this means is, controlling for the total PF ownership in a PE fund, higher same-state ownership leads to a higher amount of commitment in a private equity fund. Column 6 evaluates the herding effect for PE funds without any same-state fund commitment, and Column 7 focuses on the PE funds with at least one other same state commitment. What we can observe is, PFs significantly herd towards other PFs in the absence of other same-state peers investing in the same PE fund. However, when there are other same state funds involved, their commitment decisions override the effects coming from all other PFs, significantly shaping the commitment decisions of the pension fund of interest, and this shows how significant the competition at the state-level is.

A natural concern related to the results discussed above is the fact that in some of the states of the United States, several pension funds’ investments are managed by a state-level Investment Board, and these separate funds generally end up committing in the same private equity funds. This would definitely affect the results that we have obtained in the previous section. To control for this fact, I obtain the list of 15 states in which there is a state investment board from the Public Plans Data website (Public Plans Data, 2020) and eliminate these states from the sample. Untabulated results do not show any significant difference in the results obtained, ruling out any possible effect coming from the existence of state investment boards.

What is the direction of herding at the state-level? Do the fact that PFs herd towards similar pension funds prevail at the state level? In Panel B of Table (8), I try to find an answer to this question. Using the similar approach that I used in Table 7, I break down the variable “SameStatePFCommitShare” into two sub-components, “SameState-SPFCommitShare” and “SameStateLPFCommitShare” to evaluate the effects of commitments of small and large same-state peers separately. Unlike Table (7), I make the evaluation for two size subgroups, Small vs Large, since same-state commitment observations are sparse and although more granular evaluations provide similar results, they become harder to interpret. Panel (B) confirms the results we have obtained in the pre-

vious section, with PPFs following the similarly-sized same-state peers, and they are not affected by the commitment decisions of PPFs of different size categories. These findings support the conclusion that PPF trustees/investment teams are mainly motivated by reputational concerns while deciding on the commitment amount to a private equity fund.

[Table 8: Same-State Herding]

4.3 Do Pension Funds Benefit from Herding?

The final step in understanding the herd behaviour of PPFs is to evaluate its consequences. Do PPFs benefit from herding in their PE commitments? To find the answer to this question, I evaluate how the return of committed private equity funds change with the level of public pension fund ownership at the country and state level. The regression model of interest is:

$$NetIRR_{p,g,i,t,s} = \alpha + \beta_1 PFCOMMITSHARE_{p,g,i,t,s} + \beta_2 SAMESTATECOMMITSHARE_{p,g,i,t,s} + \gamma X_{q,i} + \theta_p + \mu_t + \nu_s + \epsilon_{p,g,i,t,s} \quad (3)$$

Overall results of these tests are presented in Panel (A) of Table (9). The commitments that are accompanied by larger ownership of other PPFs perform significantly better. These results by no means mean that PPFs perform better than other types of institutional investors in their PE investments. On the contrary, previous research mostly agrees that public pension funds do not outperform other institutional investors in their PE investments (Hochberg and Rauh, 2013; Sensoy, Wang and Weisbach, 2014). What these results suggest is, among the PE funds with at least one PPF as an investor, the ones with higher shares of PPF ownership perform better. Although evaluating the reasons for this result exceeds the scope of this paper, it shows us that PPFs are vulnerable in their PE commitments that are not guided, inspired or shared by peers. So herding towards the PE funds with bigger PPF ownership pays off for the PPFs.

The situation is completely different when it comes to same-state herding. Controlling for the total PPF ownership, private equity commitments that are accompanied by higher levels of same-state involvement perform worse. These results are robust to different model specifications. These findings are in line with the academic literature discussing the negative effects of local overweighting (Hochberg and Rauh, 2013) and political career aspirations (Andonov et al., 2018) on the PPF performance. In accordance with the literature, the results in panel (A) suggest that herding towards the same-state peers for PE fund investments is not a purely professional decision, and these investments significantly underperform.

Panel (B) of Table (9) evaluates the effect of herding on performance for PE strategy subgroups and presents the four main groups with a large enough number of observations.

Since the sample sizes are very small for the subgroups, the results are less precise, but they still highlight a consistent story. For all subgroups, we have largely negative coefficients for “SameStateCommitShare” and non-negative (and mostly significantly positive) coefficients for “PFCommitShare”, consistent with the overall picture drawn in Panel (A).

[Table 9: Herding and Private Equity Fund Performance]

5 Conclusions

Despite the growing popularity of the private equity industry among institutional investors, academic literature provides little insight on what factors institutional investors take into account while determining the amount of commitment they make to a particular private equity fund.

This paper provides new insight on the investment decisions of a particular type of institutional investor, public pension funds, by showing that they herd towards their peers in their private equity commitment decisions. The detailed analysis supports the two theoretical explanations for herd behaviour: Informational and reputational herding. In accordance with the informational herding hypothesis, investors herd more when information quality deteriorates, such as high market volatility and low market performance. Investors also herd more for funds with riskier strategies, for which the outcome of the investments has more uncertainty.

Moreover, the paper provides support for the reputational herding hypothesis. Investors herd towards similarly-sized peers, which constitute their performance benchmarks. Herding intensifies within-state, supporting the argument that pension fund trustees prioritize their political aspirations while making investment decisions. Additionally, same-state herding hurts the performance of the pension funds, in accordance with the literature documenting the negative effects of the investing decisions of politically-motivated trustees.

Several questions remain for future research. First, this paper does not assess the effect of the heterogeneity in the pension fund board trustee composition on herd behaviour. Further research documenting different herding effects from appointed, elected and ex-officio trustees would provide invaluable insight on the reputational herding hypothesis. Additionally, this study focuses on public pension funds located in the United States. Extending the sample to include other institutional investor types and other geographical locations and investigating how the herd behaviour differs with investor type and location would yield significant depth to our understanding of how institutional investors make private equity investment decisions.

References

- Andonov, A., Bauer, R. and Cremers, M. (2012) ‘Can Large Pension Funds Beat the Market? Asset Allocation, Market Timing, Security Selection and the Limits of Liquidity’, Working Paper.
- Andonov, A., Bauer, R. and Cremers, M. (2017) ‘Pension Fund Asset Allocation and Liability Discount Rates’, *Review of Financial Studies*, 30(8), pp. 2555-2595.
- Andonov, A., Hochberg, Y. V. and Rauh, J. D. (2018) ‘Political Representation and Governance: Evidence from the Investment Decisions of Public Pension Funds’, *Journal of Finance*, 73(5), pp. 2041-2086.
- Avery, C., Chevalier, J. (1999), ‘Herding over the career. *Economics Letters*’, 63(3), pp. 327–333.
- Banerjee, A. V. (1992) ‘A Simple Model of Herd Behavior’, *The Quarterly Journal of Economics*, 107(3), pp. 797–817.
- Bekiros, S. , Jlassi, M., Lucey, B., Naoui K., Uddin, G. S. (2017), ‘Herding Behavior, Market Sentiment and Volatility: Will the Bubble Resume?’, *The North American Journal of Economics and Finance*, 42, pp. 107-131
- Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992). ‘A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades’, *Journal of Political Economy*, 100(5), pp. 992–1026.
- Bikhchandani, S. and Sharma, S. (2000), ‘Herd Behavior in Financial Markets’, *IMF Staff Papers*, 47(3), pp. 279–310.
- Blake, D., Lehmann, B. N. and Timmermann, A. (1999) ‘Asset Allocation Dynamics and Pension Fund Performance’, *Journal of Business*, 72(4), pp. 429-461.
- Blake, D., Lehmann, B. N. and Timmermann, A. (2002) ‘Performance Clustering and Incentives in the UK Pension Fund Industry’, *Journal of Asset Management*, 3(2), pp. 173-194.
- Blake, D., and Timmermann, A. (2002), ‘Performance Benchmarks for Institutional Investors’, *Performance Measurement in Finance*, Butterworth - Heinemann, pp. 108-141
- Blake, D., Sarno, L., and Zinna, G. (2017) ‘The Market for Lemmings: The Herding Behavior of Pension Funds’, *Journal of Financial Markets*, 36, pp. 17-39.
- Bradley, D., Pantzalis, C. and Yuan, X. (2016) ‘The Influence of Political Bias in State Pension Funds’, *Journal of Financial Economics*, 119(1), pp. 69–91.

- Brown, J., Pollet J. and Weisbenner, S (2009), ‘The Investment Behavior of State Pension Plans’, Working Paper.
- Brennan, M. J. (1990) ‘Latent Assets’, *Journal of Finance*, 45(3), pp. 709–730.
- Cai, F., Han, S., Li, D. and Li, Y. (2019). ‘Institutional Herding and Its Price Impact: Evidence from the Corporate Bond Market’, *Journal of Financial Economics*, 131(1).
- Chang, E., Cheng, J. and Khorana, A. (2000), ‘An Examination of Herd Behavior in Equity Markets: An International Perspective’, *Journal of Banking and Finance*, 24(10), 1651–1679.
- Chevalier, J. and Ellison, G. (1999), ‘Career concerns of mutual fund managers’, *Quarterly Journal of Economics*, 114(2), pp. 389–432.
- Christie, W. G. and Huang, R. D. (1995), ‘Following the Pied Piper: Do Individual Returns Herd around the Market?’, *Financial Analysts Journal*, 51(4), pp. 31–37.
- Comtois, J. (2019), ‘Private equity fundraising, investment in Europe hits record levels in 2018’, accessed 9 March 2021, < <https://www.pionline.com/article/20190507/ONLINE/190509890/private-equity-fundraising-investment-in-europe-hits-record-levels-in-2018-report> >
- Da Rin, M. and Phalippou, L. (2017) ‘The Importance of Size in Private Equity: Evidence From a Survey of Limited Partners’, *Journal of Financial Intermediation*, 31, pp. 64–76.
- Dasgupta, A., Prat, A. (2008), ‘Information Aggregation in Financial Markets with Career Concerns’, *Journal of Economic Theory*, 143(1), pp. 83–113.
- Duygun, M., Tunaru, R., Vioto, D. (2021), ‘Herding by Corporates in the US and the Eurozone Through Different Market Conditions’, *Journal of International Money and Finance*, 110, 102311.
- Dyck, A., Manoel, P. M. and Morse, A. (2018), ‘Outraged By Compensation: Implications for Public Pension Performance’, Working Paper.
- Economou F., Hassapis C. and Philippas N. (2018), ‘Investors’ Fear and Herding in the Stock Market’, *Applied Economics*, 50:34-35, pp. 3654-3663
- Franzoni, F., Nowak, E., and Phalippou, L. (2012), ‘Private Equity Performance and Liquidity Risk’, *Journal of Finance*, 67(6), pp. 2341–2373.
- Froot, K. A., Scharfstein, D. S. and Stein, J. C. (1992) ‘Herd on the Street : Informational Inefficiencies in a Market with Short-Term Speculation’, *Journal of Finance*, 47(4), pp. 1461–1484.
- Gompers, P., and Lerner, J. (1996), ‘The Use of Covenants: An Analysis of Venture Partnership Agreements’, *Journal of Law and Economics*, 39(2), pp. 463–498.

- Graham, J. R. (1999) ‘Herding Among Investment Newsletters: Theory and Evidence’, *Journal of Finance*, 54(1), pp. 237–268.
- Hess, D. (2005), ‘Protecting and Politicizing Public Pension Fund Assets: Empirical Evidence on the Effects of Governance Structures and Practices’, *University of California Davis Law Review*, 39, pp. 187-224.
- Hirshleifer, D., Subrahmanyam, A., Titman, S. (1994) ‘Security Analysis and Trading Patterns when Some Investors Receive Information Before Others’, *Journal of Finance*, 49(5), pp. 1665–1698.
- Hochberg, Y. V. and Rauh, J. D. (2013) ‘Local Overweighting and Underperformance: Evidence from Limited Partner Private Equity Investments’, *Review of Financial Studies*, 26(2), pp. 403-451.
- Hwang, S. and Salmon, M. (2004), ‘Market Stress and Herding’, *Journal of Empirical Finance*, 11(4), 585–616.
- Jung, R.G. and Rhee, N. (2013) ‘How Do Public Pensions Invest? A Primer’, *National Institute on Retirement Security*.
- Keynes, J. M. (1936), ‘The General Theory of Employment, Interest and Money’, *MacMillan Publications*, London
- Koedijk, K., Slager, A. and Dam, J. V. (2019). ‘Achieving Investment Excellence: A Practical Guide for Trustees of Pension Funds, Endowments, Foundations’, *Wiley*, pp. 19-38.
- Morck, B., Shleifer, A., and Vishny, R. (1989). ‘Alternative Mechanisms for Corporate Control’, *American Economic Review*, 79(4), pp. 842–852.
- Lakonishok, J., Shleifer, A. and Vishny, R. W. (1992), ‘The impact of institutional trading on stock prices’, *Journal of Financial Economics*, 32(1), pp. 23–43.
- Lerner, J., Schoar, A. and Wongsunwai, W. (2007), ‘Smart Institutions, Foolish Choices: the Limited Partner Performance Puzzle’. *Journal of Finance*, 62(2),pp. 731–764
- McKinsey (2020), ‘A New Decade for Private Markets: McKinsey Global Private Markets Review 2020’, accessed 1 March 2021 ,
<<https://www.mckinsey.com/industries/private-equity-and-principal-investors/our-insights/mckinseys-private-markets-annual-review> >
- Meerkaat, H. and Liechtenstein, H. (2009), ‘Driving the Shakeout in Private Equity’, accessed 9 March 2021, < <https://media.iese.edu/research/pdfs/ESTUDIO-91-E.pdf> >

Miller, S. (2017), ‘Teacher Retirement System Awash in Bonus Cash — Yet Still Seeks Help to Fund Health Care’, accessed 3 March 2021, < <https://texasmonitor.org/teacher-retirement-system-bonus-cash-fund-health-care/> >

Musalem, A. R. and Palacios, R. J. (2004). ‘Public Pension Fund Management : Governance, Accountability, and Investment Policies’. World Bank, pp. 49-89.

National Association of State Retirement Administrators (2021a), accessed 26 January 2021, < <https://www.nasra.org/content.asp?admin=Ycontentid=200> >

National Association of State Retirement Administrators (2021b), accessed 27 January 2021, < <https://www.nasra.org/contributions: :text=Public%20pensions%20are%20financed%20primarily,from%20both%20employees%20and%20employers.> >

Novy-Marx, R., and Rauh, J. (2011), ‘Public pension liabilities: How big are they and what are they worth?’ *Journal of Finance*, 66(4), pp. 1207–45.

OECD (2020), ‘Pension Funds in Figures’, accessed 9 March 2021, < <http://www.oecd.org/pensions/private-pensions/Pension-Funds-in-Figures-2020.pdf> >

Popescu, M., and Xu, Z. (2014) ‘Does Reputation Contribute to Institutional Herding?’, *Journal of Financial Research*, 37(3), pp. 295–322.

Popescu, M., Xu, Z. (2018) ‘Mutual Fund Herding and Reputational Concerns’, *Journal of Economics and Finance*, 42(3), 550–565.

Preqin (2012) ‘Private Equity Funds of Funds’ Evolving Investment Strategies’, accessed 8 February 2021 , <https://docs.preqin.com/reports/Private_Equity_Fund_of_Funds_Strategies_May12.pdf >

Preqin (2014) ‘The Risks, the Returns and the Fundraising Successes of Private Equity Funds’, accessed 10 February 2021 , <https://docs.preqin.com/newsletters/pe/Preqin_PESL-Jul-14-Risk-Return.pdf >

Preqin (2019) ‘2019 Private Equity & Venture Capital Fundraising & Deals Update’, accessed 09 March 2021 , < <https://docs.preqin.com/reports/2019-Private-Equity-Venture-Capital-Fundraising-Deals-Update.pdf> >

Public Plans Data (2020), accessed 27 January 2021 , < <https://publicplansdata.org/wp-content/uploads/2020/06/Board-Membership.xlsx> >

Public Plans Data (2021), accessed 27 January 2021 , < <https://publicplansdata.org/quick-facts/national/> >

- Raddatz, C. and Schmukler, S. L. (2013) ‘Deconstructing Herding: Evidence from Pension Fund Investment Behavior’, *Journal of Financial Services Research*, 43, pp. 99-126.
- Rauh, J. D. (2009) ‘Risk Shifting versus Risk Management: Investment Policy in Corporate Pension Plans’, *Review of Financial Studies*, 22(7), pp. 2687-2733.
- Robinson, D., and Sensoy, B. A. (2016). ‘Cyclicality, performance measurement, and cash flow liquidity in private equity’, *Journal of Financial Economics*, 122(3), pp. 521–543.
- Scharfstein, D., Stein, J. (1990). ‘Herd Behavior and Investment’, *The American Economic Review*, 80(3), pp. 465–479.
- Sensoy, B. A., Wang, Y. and Weisbach, M. S. (2014), ‘Limited partner performance and the maturing of the private equity industry’, *Journal of Financial Economics*, 112(3), pp. 320–343.
- Trueman, B. (1994) ‘Analyst Forecasts and Herding Behavior’, *Review of Financial Studies*, 7(1), pp. 97–124.
- Welch, I. (1992) ‘Sequential Sales , Learning , and Cascades’, *Journal of Finance*, 47(2), pp. 695–732.
- Welch, K. and Stubben, S. (2018) ‘Private Equity’s Diversification Illusion: Evidence from Fair Value Accounting’, Working Paper.
- Wermers, R. (1999), ‘Mutual Fund Herding and the Impact on Stock Prices’, *Journal of Finance*, 54(2), 581–622.

Figure 1: Public Pension Fund Herding by Commitment Years

This figure presents the yearly herding coefficients obtained from the regression based on a modification of Equation (1), in which “PFCCommitShare” is interacted with commitment year dummies. The figure also presents the 95% confidence intervals, built using heteroskedasticity-robust and clustered at the LP level. Years before 2000 are omitted because of the very limited number of observations.

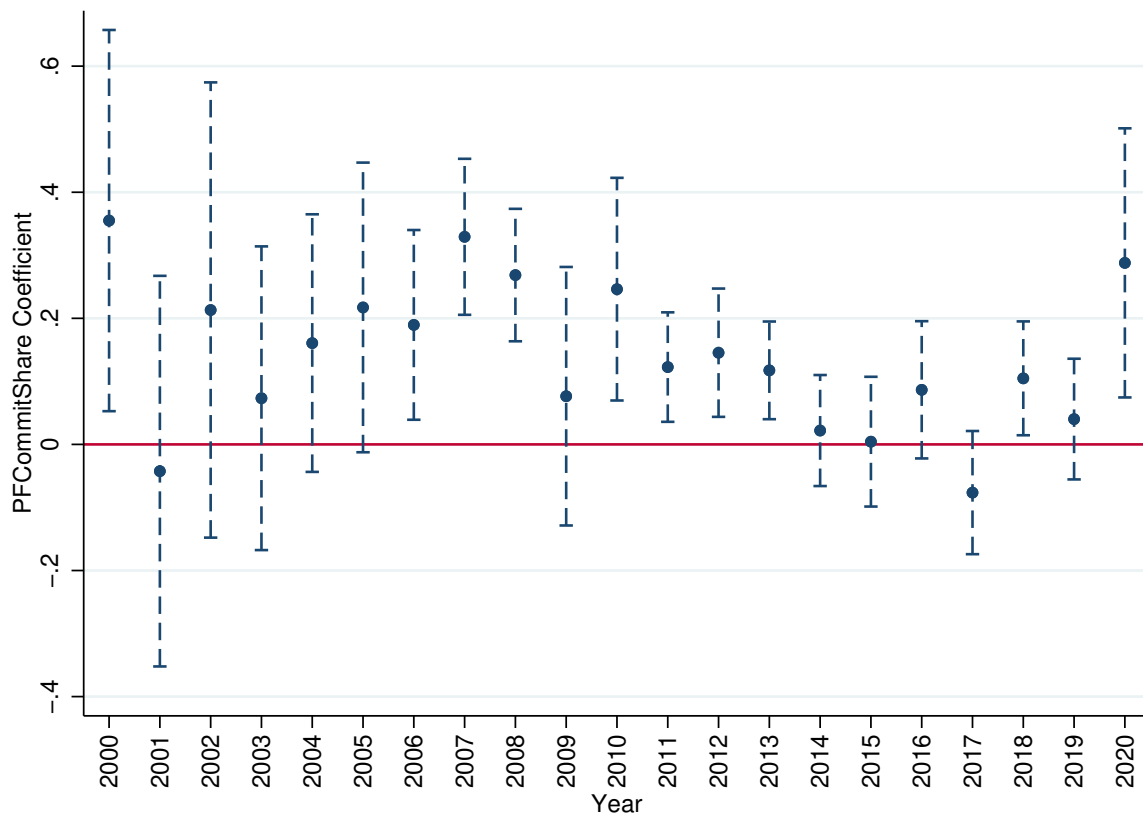


Figure 2: Public Pension Fund Herding by Private Equity Strategy

This figure presents the coefficients for “PFCommitShare” variable, obtained from the regressions based on Equation (1), ran separately for the major private equity strategy subgroups. The figure also presents the 95% confidence intervals, built using heteroskedasticity-robust and clustered at the LP level.

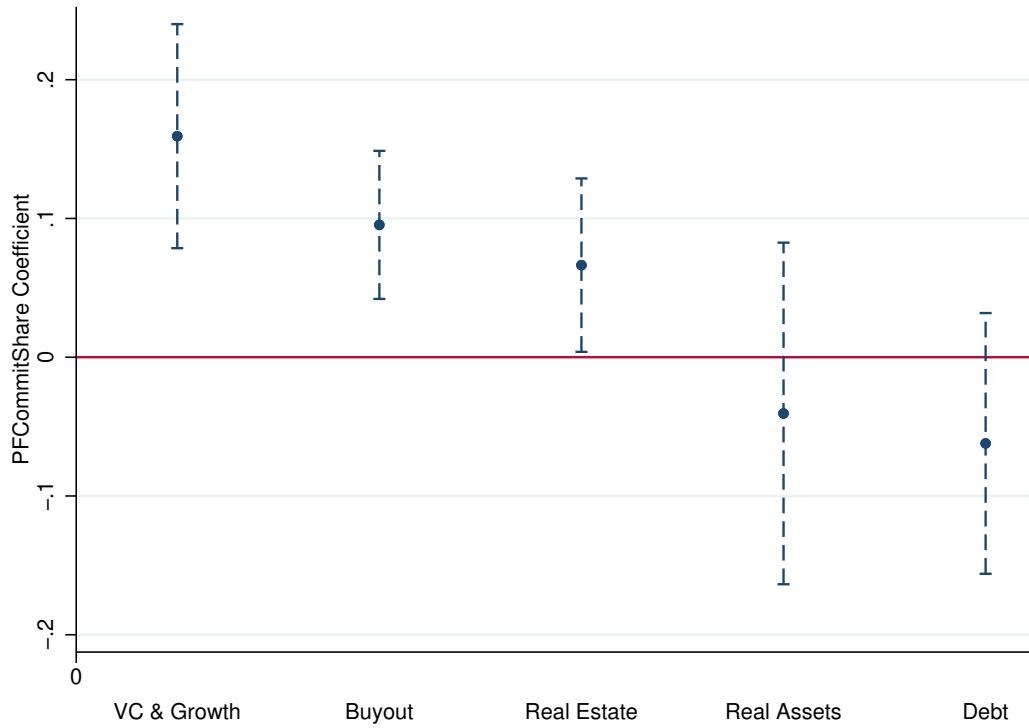


Figure 3: Herding by Fund Size

This figure evaluates the direction of the herd behaviour by presenting the coefficients for “SmallPFCommitShare” and “LargePFCommitShare” variables separately for each public pension fund size category. For working out the herding direction, a broader categorization for pension fund size is built, in which the “Small” category includes size groups 1,2 and 3, and the “Large” group comprises size groups 4 and 5. The figure also presents the 95% confidence intervals, built using heteroskedasticity-robust and clustered at the LP level.

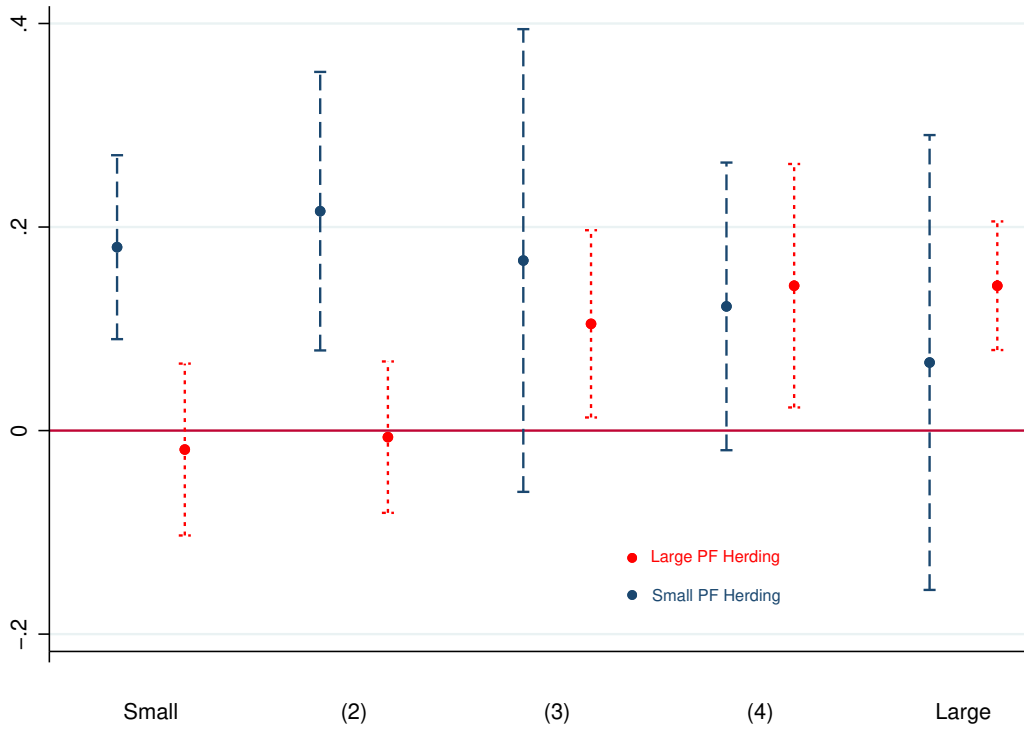


Table 1: Descriptive Statistics

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 and pension fund size. Panel B provides the same data as Panel A for the main dependent variable, “lnCommitRatio”. Panel C shows the details for the public pension fund size categories, assessed in terms of the total asset under management (“AUM”). Panel D presents the characteristics of the other important variables included in the analysis.

Panel A: Commitment Amount (\$ mn)	N	Mean	Median	SD
<i>By PE Fund Strategy</i>				
Buyout	5,586	83.7	50	107.7
Debt	2,034	70.3	49	82.1
Real Assets	986	73.9	50	81.9
Real Estate	2,142	60.5	50	61.3
VC & Growth	2,241	45.2	25	61.6
Other	1,549	43.6	25	60.7
Total	14,538	67.5	40	87.3
<i>By PPF Size Category</i>				
1	2,949	17.4	12	20.3
2	2,922	33.5	30	26.4
3	3,060	43.7	40	34.6
4	2,839	95.5	75	79.1
5	2,768	154.5	100	135.1
Total	14,538	67.5	40	87.3
Panel B: lnCommitRatio	N	Mean	Median	SD
<i>By PE Fund Strategy</i>				
Buyout	5,586	0.69	0.68	0.25
Debt	2,034	0.69	0.69	0.25
Real Assets	986	0.70	0.68	0.22
Real Estate	2,142	0.69	0.67	0.24
VC & Growth	2,241	0.53	0.51	0.25
Other	1,549	0.67	0.69	0.26
Total	14,538	0.66	0.66	0.25
<i>By PPF Size</i>				
1	2,949	0.67	0.69	0.21
2	2,922	0.67	0.68	0.22
3	3,060	0.65	0.65	0.26
4	2,839	0.66	0.64	0.29
5	2,768	0.66	0.63	0.29
Total	14,538	0.66	0.66	0.25
Panel C: Pension Fund AUM (\$ mn)	N	Mean	Min	Max
<i>By PPF Size Category</i>				
1	148	1,475	36	6,223
2	34	12,961	6,860	19,273
3	18	31,372	19,924	46,235
4	14	66,316	46,856	88,457
5	9	175,660	88,640	386,070
Total	223	16,740	36	386,070
Panel D: Other Variables	N	Mean	Median	SD
Net IRR (Vintage < 2011)	3,350	0.094	0.092	0.089
PFCommitShare	14,538	0.217	0.200	0.139
SameStateCommitShare	14,538	0.019	0.000	0.050
lnGPFundTotalSize	14,538	9.307	9.441	1.680
GPEExperienceYear	14,534	0.507	0.528	0.965

Table 2: Pension Fund Herding in Private Equity Fund Commitments

This table presents the results of the regressions in which the dependent variable is “lnCommitRatio”, a variable assessing the magnitude of a private equity commitment compared to the average commitment made during the three-year window around the year of observation. The independent variable of interest is “PFCommitShare”, which assess the total ownership share of all other public pension funds in a specific private equity fund. Other control variables are the natural logarithm of the private equity fund size, the natural logarithm of the total size of private equity funds managed by a specific general partner, and general partner experience in private equity standardized for each observation year. Limited partner, commitment year and strategy fixed effects are controlled for, under different specifications. Observations are at LP x PE Fund level. 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)
PFCommitShare	0.075*** (0.02)	0.121*** (0.02)	0.125*** (0.02)	0.129*** (0.02)	0.115*** (0.02)
lnFundSize		0.095*** (0.01)	0.095*** (0.01)	0.099*** (0.01)	0.110*** (0.01)
lnGPFundTotalSize			0.005* (0.00)	0.002 (0.00)	-0.013*** (0.00)
GPExperienceYear			-0.017*** (0.00)	-0.015*** (0.00)	-0.004 (0.00)
Limited Partner FE	No	Yes	Yes	Yes	Yes
Commitment Year FE	No	No	No	Yes	Yes
Strategy FE	No	No	No	No	Yes
Adjusted R-squared	0.002	0.185	0.188	0.192	0.227
N	14,538	14,538	14,534	14,534	14,534

Table 3: Pension Fund Herding in Private Equity Strategy Commitments

This table presents the results of the regressions in which the dependent variable is “lnStrategyShareRatio”, a variable assessing the share of yearly commitments allocated to a specific strategy by a public pension fund by comparing it to the share of the total size of private equity funds started operating during the same year, with the same strategy. The independent variable of interest is “PFCommitShareStrategy”, which assess the total ownership share of all other public pension funds in a specific private equity fund strategy. Limited partner, vintage year and strategy fixed effects are controlled for, under different specifications. Observations are at LP - Vintage Year - Strategy level. 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)
PFCommitShareStrategy	0.940*** (0.18)	0.788*** (0.13)	0.718*** (0.12)	1.084*** (0.16)
Limited Partner FE	No	No	Yes	Yes
Vintage Year FE	No	No	No	Yes
Strategy FE	No	Yes	Yes	Yes
Adjusted R-squared	0.012	0.214	0.262	0.282
N	4,691	4,691	4,691	4,691

Table 4: Public Pension Fund Herding vs Market Conditions

This table presents the results of the regressions in which the dependent variable is “lnCommitRatio”, a variable assessing the magnitude of a private equity commitment compared to the average commitment made during the three-year window around the year of observation. For Panel A, the independent variable of interest is the interaction term “PFCommitShare x SP500Change”, which aims to assess how the herding behaviour changes with the changes in S&P500 Index. In Panel B, the independent variable of interest is the interaction term “PFCommitShare x AvgVIX”, and aims to perform a similar evaluation for the VIX index. Other control variables are the natural logarithm of the private equity fund size, the natural logarithm of the total size of private equity funds managed by a specific general partner, and general partner experience in private equity standardized for each observation year. Limited partner and strategy fixed effects are controlled for under different specifications. Observations are at LP x PE Fund level. 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.

Panel A: Herding vs Changes in S&P500 Index

	(1)	(2)	(3)	(4)	(5)
PFCommitShare	0.088*** (0.03)	0.132*** (0.02)	0.137*** (0.02)	0.141*** (0.02)	0.129*** (0.02)
SP500Change	0.007 (0.02)	0.026 (0.02)	0.014 (0.02)	0.010 (0.02)	0.025 (0.02)
PFCommitShare x SP500Change	-0.178* (0.09)	-0.202** (0.09)	-0.216** (0.09)	-0.206** (0.09)	-0.266*** (0.08)
lnFundSize		0.081*** (0.01)	0.095*** (0.01)	0.095*** (0.01)	0.105*** (0.01)
lnGPFundTotalSize				0.005* (0.00)	-0.008*** (0.00)
GPExperienceYear				-0.017*** (0.00)	-0.008** (0.00)
Limited Partner FE	No	No	Yes	Yes	Yes
Strategy FE	No	No	No	No	Yes
Adjusted R-squared	0.002	0.159	0.185	0.189	0.221
N	14,538	14,538	14,538	14,534	14,534

Panel B: Herding vs Average VIX Index

	(1)	(2)	(3)	(4)	(5)
PFCCommitShare	-0.072 (0.06)	-0.031 (0.05)	-0.024 (0.05)	-0.012 (0.05)	-0.032 (0.05)
AvgVIX	-0.002** (0.00)	-0.001* (0.00)	-0.001 (0.00)	-0.001 (0.00)	-0.001 (0.00)
PFCCommitShare x AvgVIX	0.008*** (0.00)	0.008*** (0.00)	0.008*** (0.00)	0.008*** (0.00)	0.008*** (0.00)
lnFundSize		0.081*** (0.01)	0.095*** (0.01)	0.096*** (0.01)	0.106*** (0.01)
lnGPFundTotalSize				0.004 (0.00)	-0.009*** (0.00)
GPExperienceYear				-0.016*** (0.00)	-0.007** (0.00)
Limited Partner FE	No	No	Yes	Yes	Yes
Strategy FE	No	No	No	No	Yes
Adjusted R-squared	0.002	0.159	0.186	0.189	0.221
N	14,538	14,538	14,538	14,534	14,534

Table 5: Public Pension Fund Herding by Private Equity Strategy

This table evaluates herding behaviour separately for private equity fund strategies. Panel A presents the results of the regressions in which the dependent variable is “lnCommitRatio”, a variable assessing the magnitude of a private equity commitment compared to the average commitment made during the three-year window around the year of observation. The independent variable of interest is “PFCommitShare”, which assess the total ownership share of all other public pension funds in a specific private equity fund. Other control variables are the natural logarithm of the private equity fund size, the natural logarithm of the total size of private equity funds managed by a specific general partner, and general partner experience in private equity standardized for each observation year. Limited partner and commitment year fixed effects are controlled for. Observations are at LP x PE Fund level. Panel B presents the results of the regressions in which the dependent variable is “lnStrategyShareRatio”, a variable assessing the share of yearly commitments allocated to a specific strategy by a public pension fund, by comparing it to the share of the total size of private equity funds started operating during the same year, with the same strategy. The independent variable of interest is “PFCommitShareStrategy”, which assess the total ownership share of all other public pension funds in a specific private equity fund strategy. Limited partner fixed effects are controlled for. Observations are at LP x Vintage Year level. 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.

Panel A: Private Equity Fund Level					
	VC & Growth	Buyout	RE	RA	Debt
PFCommitShare	0.159*** (0.04)	0.095*** (0.03)	0.066** (0.03)	-0.041 (0.06)	-0.062 (0.05)
lnFundSize	0.166*** (0.01)	0.124*** (0.01)	0.085*** (0.01)	0.065*** (0.01)	0.058*** (0.01)
lnGPFundTotalSize	-0.024*** (0.01)	-0.011*** (0.00)	-0.009 (0.01)	0.010 (0.01)	0.003 (0.01)
GPEXperienceYear	-0.002 (0.01)	0.008 (0.00)	0.016* (0.01)	-0.017 (0.01)	-0.014 (0.01)
Limited Partner FE	Yes	Yes	Yes	Yes	Yes
Commitment Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.473	0.308	0.313	0.272	0.115
N	2,239	5,584	2,142	986	2,034

Panel B: Private Equity Fund Strategy Level

	VC & Growth	Buyout	RE	RA	Debt
PFCCommitShareStrategy	1.117*** (0.32)	0.727*** (0.17)	0.586 (0.40)	-1.146* (0.66)	-0.479 (0.36)
Limited Partner FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.195	0.267	0.220	0.354	0.236
N	1,135	1,066	738	532	777

Table 6: Public Pension Fund Herding by Fund Size Categories

This table presents the regressions evaluating the herd behaviour for public pension fund size groups. Columns represent the size groups from 1 (Smallest) to 5 (Largest). The dependent variable is “lnCommitRatio”, a variable assessing the magnitude of a private equity commitment compared to the average commitment made during the three-year window around the observation year. The independent variable of interest is “PFCommitShare”, which assess the total ownership share of all other public pension funds in a specific private equity fund. Other control variables are the natural logarithm of the private equity fund size, the natural logarithm of the total size of private equity funds managed by a specific general partner, and general partner experience in private equity standardized for each observation year. Limited partner, commitment year and strategy fixed effects are controlled for. Observations are at LP x PE Fund level. 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.

	Small	(2)	(3)	(4)	Large
PFCommitShare	0.077** (0.03)	0.060* (0.03)	0.121*** (0.04)	0.137*** (0.04)	0.127*** (0.04)
lnFundSize	0.053*** (0.01)	0.071*** (0.01)	0.101*** (0.01)	0.156*** (0.01)	0.165*** (0.02)
lnGPFundTotalSize	-0.016** (0.01)	-0.006 (0.01)	-0.013** (0.00)	-0.020*** (0.00)	-0.006 (0.00)
GPExperienceYear	-0.017** (0.01)	-0.001 (0.01)	-0.002 (0.01)	-0.002 (0.01)	0.007 (0.01)
Limited Partner FE	Yes	Yes	Yes	Yes	Yes
Commitment Year FE	Yes	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.030	0.167	0.235	0.418	0.403
N	2,948	2,922	3,059	2,837	2,768

Table 7: Public Pension Fund Herding by Fund Size Categories - Herding Direction

This table presents the regressions evaluating the direction of the herd behaviour for public pension fund size groups. Columns represent the size groups from 1 (Smallest) to 5 (Largest). The dependent variable is “lnCommitRatio”, a variable assessing the magnitude of a private equity commitment compared to the average commitment made during the three-year window around the observation year. Independent variables of interest are “SmallPFCommitShare” and “LargePFCommitShare”, which assess the total ownership share of all other small (size groups 1,2 and 3) and large (size groups 4 and 5) public pension funds in a specific private equity fund. Other control variables are the natural logarithm of the private equity fund size, the natural logarithm of the total size of private equity funds managed by a specific general partner, and general partner experience in private equity standardized for each observation year. Limited partner, commitment year and strategy fixed effects are controlled for. Observations are at LP x PE Fund level. 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.

	Small	(2)	(3)	(4)	Large
SmallPFCommitShare	0.180*** (0.05)	0.216*** (0.07)	0.167 (0.11)	0.122* (0.07)	0.067 (0.10)
LargePFCommitShare	-0.019 (0.04)	-0.006 (0.04)	0.105** (0.04)	0.142** (0.06)	0.142*** (0.03)
lnFundSize	0.058*** (0.01)	0.076*** (0.01)	0.102*** (0.01)	0.156*** (0.01)	0.164*** (0.02)
lnGPFundTotalSize	-0.014** (0.01)	-0.005 (0.01)	-0.012** (0.00)	-0.020*** (0.00)	-0.006 (0.00)
GPExperienceYear	-0.018** (0.01)	-0.002 (0.01)	-0.003 (0.01)	-0.002 (0.01)	0.007 (0.01)
Limited Partner FE	Yes	Yes	Yes	Yes	Yes
Commitment Year FE	Yes	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.035	0.171	0.235	0.418	0.403
N	2,948	2,922	3,059	2,837	2,768

Table 8: Same-State Herding

This table presents the results of the regressions in which the dependent variable is “lnCommitRatio”, a variable assessing the magnitude of a private equity commitment compared to the average commitment made during the three-year window around the year of observation. In Panel A, the independent variable of interest is “SameStateCommitShare”, which assess the total ownership share of all other same-state public pension funds in a specific private equity fund. Other control variables are the natural logarithm of the private equity fund size, the natural logarithm of the total size of private equity funds managed by a specific general partner, and general partner experience in private equity standardized for each observation year. Limited partner, commitment year and strategy fixed effects are controlled for, under different specifications. Columns 1 to 5 evaluate the relationship for the full sample. Column 6 focuses on the observations without any same-state pension fund investor, and Column 7 focuses on the observations with at least one same-state investor. Panel B works out the direction of the relationship by grouping the pension funds into two size groups as Small (size groups 1,2 and 3) and Large (size groups 4 and 5). Observations are at LP x PE Fund level. 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.

Panel A: Overall Analysis							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PFCCommitShare	0.098*** (0.02)	0.106*** (0.02)	0.109*** (0.02)	0.114*** (0.02)	0.099*** (0.02)	0.155*** (0.02)	-0.037 (0.03)
SameStateCommitShare	0.219*** (0.07)	0.185** (0.07)	0.190** (0.08)	0.177** (0.08)	0.188*** (0.07)		0.492*** (0.11)
lnFundSize	0.083*** (0.01)	0.096*** (0.01)	0.096*** (0.01)	0.100*** (0.01)	0.111*** (0.01)	0.111*** (0.01)	0.125*** (0.01)
lnGPFundTotalSize			0.005** (0.00)	0.002 (0.00)	-0.012*** (0.00)	-0.012*** (0.00)	-0.011** (0.00)
GPEexperienceYear			-0.017*** (0.00)	-0.015*** (0.00)	-0.004 (0.00)	-0.004 (0.00)	-0.006 (0.01)
Limited Partner FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Commitment Year FE	No	No	No	Yes	Yes	Yes	Yes
Strategy FE	No	No	No	No	Yes	Yes	Yes
Adjusted R-squared	0.160	0.186	0.189	0.193	0.227	0.239	0.244
N	14,538	14,538	14,534	14,534	14,534	9,816	4,718

Panel B: Analysis for Size Sub-Groups

	Small PF	Large PF
PFCCommitShare	0.098*** (0.02)	0.097*** (0.03)
SameStateSPFCommitShare	0.372*** (0.11)	0.092 (0.24)
SameStateLPFCommitShare	-0.163* (0.09)	0.547*** (0.14)
lnFundSize	0.079*** (0.01)	0.163*** (0.01)
lnGPFundTotalSize	-0.012*** (0.00)	-0.014*** (0.00)
GPExperienceYear	-0.008* (0.00)	0.003 (0.01)
Limited Partner FE	Yes	Yes
Commitment Year FE	Yes	Yes
Strategy FE	Yes	Yes
Adjusted R-squared	0.142	0.408
N	8,929	5,605

Table 9: Herding and Private Equity Fund Performance

This table presents the results of the regressions in which the dependent variable is “Net IRR”, a variable assessing the private equity performance. Independent variables of interest is “PF-CommitShare”, which assess the total ownership share of all other public pension funds in a specific private equity fund, and “SameStateCommitShare”, which assess the total ownership share of all other same-state public pension funds in a specific private equity fund. Other control variables are the natural logarithm of the private equity fund size, the natural logarithm of the total size of private equity funds managed by a specific general partner, and general partner experience in private equity standardized for each observation year. Limited partner, commitment year and strategy fixed effects are controlled for, under different specifications. Observations are at LP x PE Fund level. Panel A presents regressions on the full sample, and in Panel B, private equity fund strategies are evaluated separately. 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.

Panel A: Overall Analysis					
	(1)	(2)	(3)	(4)	(5)
PFCCommitShare	0.093*** (0.01)	0.087*** (0.01)	0.083*** (0.01)	0.066*** (0.01)	0.056*** (0.01)
SameStateCommitShare	-0.169*** (0.03)	-0.132*** (0.02)	-0.090*** (0.03)	-0.083** (0.03)	-0.093*** (0.03)
lnFundSize	0.005*** (0.00)	-0.013*** (0.00)	-0.013*** (0.00)	-0.010*** (0.00)	-0.016*** (0.00)
lnGPFundTotalSize		0.020*** (0.00)	0.020*** (0.00)	0.019*** (0.00)	0.023*** (0.00)
GPExperienceYear		-0.012*** (0.00)	-0.012*** (0.00)	-0.013*** (0.00)	-0.012*** (0.00)
Limited Partner FE	No	No	Yes	Yes	Yes
Vintage Year FE	No	No	No	Yes	Yes
Strategy FE	No	No	No	No	Yes
Adjusted R-squared	0.025	0.090	0.095	0.189	0.233
N	3,350	3,348	3,348	3,348	3,348

Panel B: Analysis for PE Strategies

	VC & Growth	Buyout	RE	Debt
PFCCommitShare	0.005 (0.02)	0.035* (0.02)	0.109** (0.05)	0.113** (0.05)
SameStateCommitShare	-0.095 (0.10)	-0.199*** (0.07)	-0.195 (0.14)	-0.235** (0.10)
lnFundSize	-0.023*** (0.01)	-0.035*** (0.01)	-0.021** (0.01)	0.013*** (0.00)
lnGPFundTotalSize	0.033*** (0.00)	0.037*** (0.00)	0.027*** (0.00)	0.005 (0.00)
GPExperienceYear	-0.014*** (0.00)	-0.008*** (0.00)	-0.015*** (0.01)	-0.012*** (0.00)
Limited Partner FE	Yes	Yes	Yes	Yes
Vintage Year FE	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.417	0.313	0.289	0.412
N	686	1,254	445	408