Article:

Buchner, A, Mohamed, A orcid.org/0000-0002-2974-9467 and Schwienbacher, A (2020) Herd behaviour in buyout investments. Journal of Corporate Finance, 60. 101503. ISSN 0929-1199

https://doi.org/10.1016/j.jcorpfin.2019.101503

Herd behaviour in buyout investments

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This version: June 28, 2019

ABSTRACT
In this study, we explored the presence of correlated investment choices (i.e., herd behaviour) among international buyout funds by distinguishing among the contemporaneous and the following herding of smaller funds towards the top market players (i.e., the top quartile in terms of the fund size). In our analyses, we found that the industry herding towards the largest ones is common in private equity (PE) but mostly during market contractions or the deterioration of general market conditions. Moreover, we also found that as capital inflows into the PE industry slow down, herding occurs more often. This finding is consistent with the increasing competition for new capital fundraising in downturns, which can induce PE funds to herd more. We also found that both the types of herding generate higher fund returns and lower risk for funds that are capable of herding. Additionally, we documented the persistence in herding.

Keywords: Herd behaviour; buyout; private equity; performance; risk

JEL Classifications: G24; G23

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1. Introduction

Institutional investors often herd (Grinblatt, Titman, and Wermers, 1995; Koch, 2017; Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999), i.e., they invest in similar assets simultaneously, leading to similar strategies and, hence, similar outcomes. Herding may be either intentional (when investors follow others instead of relying on their own information), or unintentional (when all the investors share the same information so that the investment decisions become correlated) (Kremer and Nautz, 2013). While herding often occurs in the mutual fund industry, evidence is still missing concerning herding in the buyout industry. Therefore, we aimed to help close this gap in the literature on the buyout industry. In particular, we studied herding behaviour of smaller private equity (PE) funds towards larger and more established ones, as these are often considered to have less expertise, and adopt different risk profiles (Giot, Hege, and Schwienbacher, 2014).

Herding can have a significant economic impact because it magnifies the shifts in the financial markets (see Bikhchandani and Sharma, 2000, for a comprehensive review). Herding behaviour may explain why industry waves occur in PE, ultimately affecting the valuations of the deals in the industry (Gompers and Lerner, 2000). While industry waves are largely driven by the opportunities of technological innovation in venture capital (and, thus, are exogenously driven to a large extent), they are also apparent in the buyout industry. For instance, Harford, Stanfield, and Zhang (2015) found that the acquisitions by PE funds predict more LBOs and strategic M&As in the same industry, which may lead to waves. Moreover, empirical evidence indicating the existence of persistence in the performance of the top players in the PE industry (Kaplan and Schoar, 2005; Harris, Jenkinson, Kaplan and Stucke, 2014; Korteweg and Sorensen, 2014) may in particular induce smaller players to herd towards the more established incumbents as a way to ensure higher performance as well.

Moreover, herding seems to have greater implications in the PE industry than the mutual fund industry as the PE fund managers need to be actively involved in the target companies, and disinvestments are not possible on short notice. Moreover, any investment requires strong involvement for several years (Cumming, 2008; Kaplan and Schoar, 2005); therefore, portfolio rebalancing is not possible, unlike in the case of mutual funds, where investments are made in tradable securities. Thus, herding in PE may have a substantial impact if herding leads to inefficient investment decisions. Therefore, it is crucial to understand what drives herding, especially towards the top industry players who may lead the group. Given the many differences between mutual funds and PE funds, it is important to investigate PE separately, as the results of mutual funds cannot be generalised to PE investments.

Different theories exist that help explain the herding by fund managers. Intentional herding occurs when investors ignore their own information and “mimic” the investment choices of others because they believe those others trade on private information (Banerjee, 1992), which can lead to informational cascades (Bikhchandani, Hirshleifer, and Welch, 1992; Welsh, 1992). Another reason herding occurs is that managers are compensated according to their performance relative to that of their industry peers (Chevalier and Ellison, 1999). Such compensation schemes induce individual investors to undertake similar strategies as a way to avoid underperforming compared to their peers (Gümbel, 2005; Maug and Naik, 2011). This may especially be the case in downturns, when less capital is flowing into the PE industry. While, relative performance compensation, to the best of our knowledge, is not directly used in PE, the fact that PE firms need to raise follow-up funds every few years leads to the comparisons with their peers during the fundraising process. In particular, this may occur in downturns when less capital is flowing into the PE market, thereby enlarging the competition between the PE firms. Therefore, herding towards the top industry players may become more important. Moreover, herding may also occur unintentionally, as new and value-relevant information becoming public and all the investors reacting to this information simultaneously leads to efficient informed trading. (This is consistent with the efficient market theory in finance, which originated in the work of Fama (1970)). As a result, herding may sometimes improve market efficiency and investment returns; whereas, at other times, it may cause harm depending on the underlying reason for the herding behaviour.

The objective of this paper was to assess the risk and return impact of herding in the buyout industry. While the literature suggests several ways to measure herding (Koch, 2017; Lakonishok, Shleifer, and Vishny, 1992), not all are applicable to PE. Therefore, we followed the methodology of Koch (2017) and derived two fund-level measures of herding, each of which focused on different timings of herding, namely, contemporaneous and following (i.e., one year behind the trend).[1] In the first case, funds mimic the strategy of peers contemporaneously, while in the second case, funds follow others but with a lag. We used these two measures to explore the herding of buyout funds at the industry level. Intuitively, it measured the direction in which the PE manager is changing their portfolio relative to the benchmark funds by using an un-centred correlation coefficient. For each fund in our sample, we measured the average herding behaviour over the commitment period. A positive value of the herding measure indicates that a fund, on average, is changing her portfolio similar to the benchmark. Additionally, we considered the top 25 quartile PE funds in terms of size as our benchmark to compute the contemporaneous and the following herding measures. Hence, we measure herding in comparison with the top players in the market.

We applied this methodology on a large sample of international buyout funds covered by the Centre of Private Equity Research (CEPRES) database. The final sample includes 878 distinct buyout funds. As the database included detailed information on each portfolio company included in these 878 funds, we were able to calculate the fund-level internal rate of return (IRR) and the volatility of returns as the measures of performance and risk.

We found that both the types of herding are driven by market conditions during the year of fund inception (often called "vintage year"), such as the overall capital commitments to the PE industry worldwide, the number of PE deals made by the industry, and the number of IPOs done (which represents one way for the PE funds to exit). We also found that herding increases when market conditions deteriorate, which is consistent with the view that under higher risks, PE managers avoid unique strategies that can make it more difficult to raise follow-up funds and where investment risks could be the highest due to more difficult market times. Moreover, fund-specific characteristics such as experience, fund size, and reliance on syndication also affect herding, but the manner may differ depending on the

[1] Koch (2017) also computes a leading herding measure, which captures trendsetting. Since we focus on smaller funds possibly herding towards more established ones, we did not consider this third measure.

type. While larger funds are more likely to herd contemporaneously than to follow (i.e., following herding), funds with less experience tend to be followers. Both the types of herding appear to offer better outcomes, since they both lead to higher fund performance and lower risks. A one-standard deviation increase in contemporaneous (following) herding is associated with a 2.8% (4.7%) increase in fund return (gross of fees) annually which is economically significant. Furthermore, we documented that both types of herding behaviour displayed by the smaller funds are highly persistent among the subsequent funds managed by the same fund management firm. Therefore, given the results on performance and risk, private information and managerial skills seem to be at play, particularly as these help generate benefits from herding. If skills were not needed, everyone would herd towards the largest funds.

We also conducted several robustness checks that lead to similar results. First, in the analysis, we excluded the funds used to calculate the benchmark, which we included in our baseline analyses. The inclusion of these funds could affect our results on performance and risk implications. However, our robustness checks showed that this is not the case. Second, we performed the analysis using an alternative performance measure. Indeed, our analysis was based on IRR, which is not a risk-adjusted measure; therefore, we performed the analysis with the commonly used Public Market Equivalent (PEM) measure. Similarly, standard volatility may not capture risk properly for PE, where downside risk is a particularly important component; therefore, we reran the analysis on the risk impact by using downside volatility only. In both the cases, we obtained qualitatively similar results. Finally, we ran the analysis on the subsample of US funds only, given that the US may be a more integrated market and, thus, funds are more likely to be exposed to similar market conditions. Once again, the results we obtained for this subsample were similar to the international sample used.

The extant literature documents the herding behaviour in financial markets but not in PE. Research on herding in financial markets is typically restricted to institutional investors investing in tradable securities, where buying and selling decisions are more easily observed and made in highly liquid markets (Grinblatt, Titman, and Wermers, 1995; Lakonishok, Shleifer and Vishny, 1992; Wermers, 1999). Wermers (1999) found that while mutual funds' herding is not that common in the “average” stocks, it is common in small stocks and growth-oriented mutual funds. From the evidence he found of higher returns from herding in some strategies, he concludes that herding contributes to a more efficient price-adjustment process of stock markets. Furthermore, Kremer and Nautz (2013) conclude that while the herding of financial institutions takes place on a daily basis, it is largely unintentional, which could be a result of using similar risk models. Moreover, Koch (2017) found that a group of mutual funds leads the industry by trading before the others, which lets them generate more returns. This, he concludes, is consistent with the group of mutual funds receiving signals in advance of the other market participants and, thus, executing informed trading. We contribute to this strand of literature by examining the herding in PE, a market that is largely illiquid and, thus, different from the markets investigated so far in the literature. We modified Koch's measure to apply it to PE in order to assess the herding in buyout and its impact on fund-level risk and performance. Additionally, in contrast to the existing studies on herding, we explored the herding behaviour of smaller and less established funds as it is something we are capable of distinguishing, which is crucial to PE.

Furthermore, we contribute to the literature on the PE portfolio composition (Bernile, Cumming, and Lyandres, 2007; Kaplan and Stromberg, 2009). Bernile, Cumming, and Lyandres (2007) show that active fund managers face a trade-off between larger portfolios and higher average company values (see also Kanniainen and Keuschnigg, 2003). Through our study, we provide evidence that the PE fund managers also take the investment behaviour of their peers into account in their own portfolio composition. On a related note, previous studies have examined the impact of specialisation versus diversification on the PE and hedge funds as well as performance persistence, although their findings on which strategy is the best are contradictory (Buchner, Mohamed, and Schwienbacher, 2017; Cressy, Munari, and Malipiero, 2007; Cumming, Dai, Haß, and Schweizer, 2012; Humphery-Jenner, 2012; Knill, 2009; Shawky, Dai, and Cumming, 2012). This suggests that the results are likely to be context-specific, depending on whether it is venture capital or buyout.

The remainder of the paper proceeds as follows: Section 2 outlines the methodology based on Koch's (2017) framework, which we adapted for the illiquid PE market; Section 3 describes the data and discusses the summary statistics of the sample; Section 4 presents the analyses and the several robustness checks; and finally, Section 5 provides the conclusion.

2. Methodology

We adopted a framework developed by Koch (2017) for mutual funds based on Euclidean geometry in order to measure the similarity of portfolio decisions in the PE industry at the fund level. We measured the direction in which the managers are changing the industry exposure of their portfolio compared to a benchmark of the top market players, which we identify as the PE funds belonging to the top quartile distribution based on the fund size of the committed capital. To construct our benchmark for the herding measure, we sorted all the PE funds for each vintage year based on the size of their committed capital. Then, we used the top quartile PE funds of each vintage year as our benchmark to compute the contemporaneous and the following herding measures. This approach allowed us to calculate the time-varying herding behaviour for the PE funds, including the benchmark funds. (When the robustness checks were conducted, similar results were derived without the funds used to compute the benchmark.)

For each PE fund, we measure the similarity in the investment decisions of the fund managers with two timing structures, generating measures of contemporaneous and following herding. Throughout the study, we adopted the same wordings as used employed by Koch for these two types of herding. Therefore, we refer to contemporaneously similar investment decisions as contemporaneous herding, or investment patterns that are going towards a direction similar to that of the benchmark's current investment decisions. Similarly, following herding refers to the investment patterns in which the given fund invests after the benchmark. In the analysis detailed below, we used a lag of one year.

Each PE fund portfolio can be thought of as having a "location" that is determined by its portfolio company investments in different industries. Moreover, as the fund makes new portfolio company investments, the location of the portfolio changes. The location of a portfolio and the direction in which it is moving can be easily measured by comparing it to the benchmark. The direction to which the portfolio moves over time compared to that of its peers reflects the extent to which the manager's investment decisions are similar to those of the benchmark funds.

To formalise these ideas, we denoted the vector of the portfolio industry weights for the fund f at quarter t by $w_{f,t}$, where each element of the vector represents the weight of a specific industry in the fund's portfolio. For each fund $f = 1, 2, \ldots, F$, the benchmark portfolio had portfolio industry weights denoted by the vector $h_{f,t}$, where each element equals the average portfolio weight among funds in the same industry as defined for vector $w_{f,t}$ (excluding the fund f). The terms $w_{f,t}$ and $h_{f,t}$ are vectors of holding levels and represent the location of the fund and its benchmark at time t, respectively. Motivated by Koch (2017), we used the cosine of the angle (θ) between the changes in these two vectors over time to measure the similarity in their investment decisions. The measure of contemporaneous herding (the variable *Contemp herding*) in investment behaviour is defined in the following manner:

$$Contempherding_{f,t} = \cos(\theta) = \frac{\Delta w_{f,t} \bullet \Delta h_{f,t}}{\left\| \Delta w_{f,t} \right\| \left\| \Delta h_{f,t} \right\|}$$

The cosine function in the equation has the advantage of transforming the angle into an un-centred correlation coefficient. The use of an un-centred correlation is more appropriate in our setting than a typical correlation coefficient because the portfolio weight changes are constrained in that they sum up to 0. Therefore, the higher the contemporaneous herding measure, the stronger is the herding behaviour of the fund f at time t. Typically, PE funds have a pre-defined period within which the fund can make new portfolio company investments; this is known as the investment period of the fund. This investment period usually lasts four to five years, while the full lifetime of a fund is generally 10 to 12 years.[2] To measure the overall herding behaviour of the fund f, we calculated the average of the quarterly contemporaneous herding measure over the typical investment period of a PE

[2] This is one of the main differences between PE funds and Mutual funds.

fund of over five years. Moreover, we considered herding in the investment decisions and not in the exit (i.e., divestment) behaviour of the PE funds.

Similarly, we constructed the following herding measure by computing the direction of a fund's investments compared to the benchmark of the prior period's investments. To calculate the benchmark of the prior period's investments, we defined the length of one period as one year. The measure of *following herding* in investment behavior is defined as follows:

$$Followingherding_{f,t} = \frac{\Delta w_{f,t} \bullet \Delta h_{f,t-4}}{\left\| \Delta w_{f,t} \right\| \left\| \Delta h_{f,t-4} \right\|}$$

For the implementation of the above equation, we calculated the herding on a quarterly basis over the lifetime of a fund, which is similar to the contemporaneous herding measure. Then, we calculated the average of the herding measures over the typical investment period of five years to determine the overall following herding behaviour of the fund f.

3. Data and summary statistics

3.1. Data

The dataset used in this study came from CEPRES. The unique feature of this database is that is contains detailed information at the fund level and on all the individual portfolio company investments undertaken by a fund, which includes the exact timing, performance, and industry of each of them. This unique feature of the data enabled us to construct the herding measures developed previously, which was essential to explore the determinants of herding behaviour of the PE funds and estimating the relationship between the fund-level herding and performance. Other studies have also used the CEPRES database (e.g., Buchner, Mohamed, and Schwienbacher, 2017; Cumming, Schmidt, and Walz, 2010;

Cumming and Walz, 2010; Franzoni, Nowak, and Phalippou, 2012; Krohmer, Lauterbach, and Calanog, 2009).

The CEPRES database collects monthly cash flow data for a large range of PE firms at the deal and fund levels. The database has detailed information related to individual deals, funds, and management firms. Moreover, these data are anonymised and, therefore, there is no incentive for PE firms to overstate or understate their performance. This is important for database providers, but, unfortunately, other databases ignore the importance of anonymity. A lack of anonymity can encourage PE firms to only provide information on better performance and suppress poor performance. Buchner, Mohamed, and Schwienbacher (2017) provide detailed discussions of the CEPRES data collection process, the information available on PE firms, and how the database compares with other databases on PE funds.

CEPRES granted us access to the information on all the funds and their portfolio company investments as of December 2017. Our analysis focused on buyout funds rather than venture capital funds because herding behaviour is primarily relevant to buyout investments as they target all the industries. In contrast, venture capital investments are concentrated in high-tech industries, and their limited partnership agreements significantly restricts their ability to invest in industries other than those contractually agreed on with limited partners. Additionally, we excluded mezzanine funds from our analysis because mezzanine funds tend to mix between equity and debt, while buyout funds focus only on equity.[3] After this filtration, we were left with a comprehensive sample of 878 international buyout funds that invested in 14,992 portfolio companies. The earliest portfolio investment in our sample started in 1975 and the most recent in 2017. We used the portfolio companies' data to calculate our herding measures with the exact timing of funds' investments.

[3] In the context of PE, herding is mostly relevant at the time of investments rather than at the time of exits. Factors other than market conditions also influence exit decisions, including the duration for which the PE firm held the portfolio company. Thus, PE fund managers have a lower margin in timing their exits than their investments.

3.2. Summary statistics

Table 1 reports the sample statistics for all the variables by mean, median, standard deviation, minimum, and maximum values. It shows that the maximum value of herding was 0.775, and the minimum value was –0.798. It also shows that during the sample period, contemporaneous herding (with similar trading patterns) has an average value of 0.042 and a median value of 0.052. Similarly, the average value of following herding is 0.010, and the median value is 0.009. These results suggest that the average un-centred correlations of investment decisions between the funds and the benchmark was 4.2% when using contemporaneous herding and 1% when using following herding. In other words, for a given fund in a given period, 4.2% or 1% of the fund investments are more likely to be on the same side as the benchmark than would be predicted if the fund investment decisions were taken randomly.[4] While the mean values were close to 0, the great variation around these mean values hint at the idea that herding occurs often, although in the opposite direction as well. These results are comparable to the average herding behaviour of mutual funds as reported by Koch (2017). In our sample of funds, the average IRR was 31.3% with a median of 27.0%. It should be noted that these performance figures are the reported gross of management fees as well as carried interest payments and, therefore, do not represent the returns earned by the fund investors (i.e., the limited partners). The finding that the mean is higher than the median (although only marginally) indicates that the distribution of returns is positively skewed and deviates from a normal distribution, which is a common feature of PE investments (Cochrane, 2005).

To assess how herding affects fund risks, we constructed a measure of risk for our sample of international buyout funds. Our measure of risk was the intra-fund volatility of IRRs. For a fund that has invested in N portfolio companies with returns IRR_1, IRR_2 and IRR_N, as measured by the IRR, this risk measure is calculated in the following manner:

[4] In our herding measures, the portfolio weight changes sum up to 0 and the levels sum up to 1. Hence, using the standard correlation is likely to overstate the significance of the herding measures, since portfolio weights or changes in weights might not be independent observations. Therefore, we use un-centred correlation, which is more appropriate in controlling such effects than a typical correlation coefficient similar to Koch's (2017).

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(IRR_i - IRR)^2},$$

Here, IRR is the mean rate of return for all the N investments made by the fund. This measure corresponds to the standard deviation of the IRRs of the individual investments made by the fund. It functions as a proxy for the variability or dispersion of the investment returns of a fund around the mean value. Thus, the funds that take on high levels of investment risk, on display, display higher levels of volatility than funds that take on low levels of risk.

However, the limitation of the standard volatility measure is that it treats positive and negative deviations from the mean return as equally undesirable risks. In fact, volatility can be the measure of risk only for normally distributed returns (Tobin 1958), which is unlike the downside volatility measure that takes the asymmetric return distributions into account by considering only the negative deviations from a pre-specified target return. Moreover, Markowitz (1991) argues that downside volatility is a more plausible measure of risk than standard volatility because investors worry about under-performance rather than over-performance. Hence, downside risk is meaningful not only from an individual investor's perspective but also from the perspective of asset pricing. We calculated downside volatility in the following manner:

$$\sigma_{Down} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\min\left(IRR_i - Tar, 0\right)\right]^2}$$

Here, *Tar* denotes the return target. Following Ang, Chen and Xing (2006), we used a target return of zero in calculating the downside volatility.

Table 1 represents the statistical data for the risk measure. According to the table, the average volatility of funds was approximately 75.8%, which is much higher than the stock returns volatility. Moreover, in our sample, the average number of portfolio companies in which the PE funds invested is 17, with a median of 13 and a maximum of 216 portfolio companies. Furthermore, the mean fund sequence number was 7.32 with median of 3.09.

This suggests that the PE funds in our sample have previously raised more than seven funds on average. Additionally, the mean value of the natural logarithm of the fund size in our sample was 25.485. The fraction of PE syndication had an average value of 59.5% on average and a median value of 48%. The mean and median natural logarithms of the capital committed to buyout funds across the globe in the vintage year of the funds are 10.565 and 10.61 (in USD millions), respectively. The average number of PE-backed deals in the vintage year of the sample funds is 613, while the average number of PE-backed IPOs in the vintage year of the sample funds is 157.

[Table 1 About Here]

Table 2 shows the correlation matrix of the variables. It is evident from the table that multicollinearity is not an issue, given the lack of excessive correlations between the explanatory variables.

[Table 2 About Here]

4. Empirical results

In this section, we first focus on understanding the determinants of the correlated investment patterns (i.e., our herding measures). Then, an examination of whether herding among PE firms influences the performance of the PE funds is presented in Section 4.2. Afterwards, the impact on risk is provided in Section 4.3. Later, an investigation of whether herding is persistent among subsequent funds for any given PE firm is provided in Section 4.4. Finally, a discussion on the further analyses performed to demonstrate the robustness of our results has been provided in Section 4.5.

4.1. Determinants of herding

We examined the determinants of herding behaviour towards the largest PE funds (i.e., our benchmark) by using fund characteristics and market variables. We considered two measures of herding: (1) contemporaneous herding, and (2) following herding.

Contemporaneous herding occurs when managers receive signals of future profitability that are not yet priced. Therefore, their investment activity might be correlated owing to the fact that the signals themselves are correlated, which leads to unintended herding. Wermers (1999) found empirical support to suggest that contemporaneously correlated trading results from the information. On the other hand, following herding behaviour is related to investment decisions based on the top peers, along with a time lag. Typically, such behaviours might not necessarily be valuable when the information on investments of the benchmark is already incorporated into prices of possible future deals. Therefore, our goal here was to understand the impact of market conditions on herding behaviour. Throughout the different analyses, we controlled the different fund characteristics and included vintage-year fixed effects.

Panel A of Table 3 shows the determinants of contemporaneous herding. Given the high correlations among the market variables, we examined their impact on herding separately. As is evident from the table, contemporaneous herding is negatively related to the total capital committed to buyout funds, number of PE-backed deals, and number of PE-backed IPOs. Thus, the market conditions help explain contemporaneous herding among buyout fund managers, and such behaviours decrease during “hot” market conditions (i.e., the times in the business cycle when there are significant inflows of capital into the PE industry occur). This result is notable in light of the literature on the cyclical nature of PE performance and capital inflows. Previous research found empirical evidence of a counter-cyclicality in fundraising conditions and investment performance (e.g., Gompers and Lerner, 2000; Kaplan and Schoar, 2005; Kaplan and Stromberg, 2009), i.e., the performance of the PE investments initiated in the boom years is significantly worse than that of the investments initiated in bust periods. The pioneering work of Gompers and Lerner (2000) suggests that this form of performance cyclicality is most likely due to the imperfections of the PE market. Moreover, they argue that high inflows could result in greater competition between PE funds for attractive deals because of the segmentation and stickiness of the PE market. In this regard, they hypothesise that fund performance suffers whenever too much money chases too few deals, as the increased competition that goes along with high capital inflows into private funds can increase the valuations and negatively affect the investment performance. Our results add to literature by showing that buyout funds may anticipate the negative impact of high capital inflows on the investment performance by attempting to invest in different industries than their benchmark did (i.e., they herd less on average during “hot” market periods). Moreover, fund characteristics such as fund size and the sequence number also have a significant impact on contemporaneous herding behaviour. The results demonstrate that fund size and sequence number are positively related to contemporaneous herding, while the fraction of syndication has a negative impact on herding. This latter relationship indicates that herding behaviour among the PE funds is not simply a result of syndication; it is also consistent with the fact that PE funds typically offer expertise in the syndicated deals, which is not the case for herding behaviour. Additionally, the results indicate that the ability to engage in contemporaneous herding is higher for funds that are large and experienced in terms of the number of previous funds managed. Funds that are large and experienced tend to have more human and capital resources to carefully analyse the market. Therefore, their ability to engage in contemporaneous herding, on average, is high.

Panel B of Table 3 demonstrates that the determinants of following herding, which is based on the same specifications as Panel A. Models 1–3 show that following herding is also has a significant negative relationship to the number of PE-backed deals and the number of PE-backed IPOs, which is, again, consistent with the view that buyout funds intentionally decrease their herding behaviour towards the benchmark during “hot” market conditions because they anticipate that too much money may be chasing too few deals. Similar to contemporaneous herding, the fund size also significantly and positively affects following herding but the sequence number has negative impact on this type of herding. Our regression results show that syndication has significant negative effects on following herding.

[Table 3 About Here]

Overall, our findings indicate that herding behaviours among PE funds are jointly determined by fund characteristics and market conditions. Moreover, the results provide consistent evidence that herding behaviour is reduced during “hot” market conditions, possibly to avoid the problem of "money-chasing deals". One reason for this reduced herding behaviour could be the relative performance evaluation. While fund compensation is not linked to relative performance in PE (Chung et al., 2012), the need to secure follow-up funding in new funds (i.e., limited partnerships) leads the managers to be compared with their peers, as the managers who perform better than their peers will attract more follow-up funding. Indeed, limited partners may reconsider their future commitments for a specific fund manager if their fund underperforms in the industry, despite having generated positive returns.

4.2. Impact of herding on performance

We examined whether herding behaviour is related to the performance of buyout funds. We expected to find a positive impact on subsequent performance if the herding was due to correlated information and a negative impact on performance if the herding was due to agency problems or any other non-informational reason, as the fund managers would push the prices away from the fundamentals. Moreover, we examined the extent to which herding behaviour affects investment performance by analysing its impact on realised fund IRRs. Panel A of Table 4 shows the impact of contemporaneous herding behaviour on IRRs. The buyout funds involved in contemporaneous herding were able to generate greater performance. Furthermore, the evidence is statistically significant at the 5% conventional level. An increase of one standard deviation in contemporaneous herding is associated with a 2.9% increase in fund return in annual terms, which is economically significant. This lends support to the view that contemporaneous herding of buyout funds is an outcome of informational advantages or skill. Additionally, the findings show that controlling for the number of portfolio companies, the fund sequence number, fund size and fraction of syndication does not explain the positive relationship between the performance and contemporaneous herding (Models 2).

In Panel B of Table 4, the results for following herding are reported. Models 1–2 show a positive impact of following herding on the performance, when controlled for fund characteristics. Moreover, the positive impact remained robust, when controlled for fund characteristics. Additionally, an increase of one standard deviation in following herding is associated with 4.69 to 5.76% increase in fund returns. Therefore, the results are statistically and economically significant.

Overall, the results show that herding has a positive impact on the performance; i.e., the incentive to herd in buyout funds is strong in both contemporaneous and following herding. Additionally, the results show that the incentive to herd is higher for following herding than for contemporaneous herding. In fact, as the results indicate, PE fund can increase their returns by twofold by herding following their benchmark instead of herding with their benchmark contemporaneously.

[Table 4 About Here]

4.3. Impact of herding on risk

We attempted to understand how herding behaviours affect fund-level risk as measured by fund volatility. Considering the effects of volatility allowed us to test whether herding behaviour also affects fund-level risk.

Panel A of Table 5 shows the impact of contemporaneous herding on volatility. Models 1–2 show strong evidence supporting that contemporaneous herding leads to lower risk when controlled for different fund characteristics. Moreover, Model 1, shows that an increase in contemporaneous herding decreases fund risks, which is statistically and economically significant. An increase of one standard deviation in herding decreases the risk by over 11%. However, when controlled for fund characteristics, a unit increase in standard deviation decreases the risk by 2.27%.

Panel B of Table 5 reports the results of following herding on risk. As Models 1–2 show, following herding has negative significant impact on risk. An increase of one standard deviation in the following herding decreases the fund risk by 11.7%, which is consistent with the results reported in Panel A. The reduction in risk was over 8.9%, with fund characteristics such as the number of the PE portfolio company, sequence number, fund size, and fraction of syndication controlled.

Overall, the results reported in Table 5 shows that contemporaneous and following herding have a negative impact on the risk exposure of buyout funds. Moreover, the results reported in Table 4 on performance further indicate that there is a significantly positive impact of herding as measured by contemporaneous or following on the performance. Thus, contemporaneous and following herding significantly enhances the performance of buyout funds and decreases the risk exposure of the funds. Additionally, the results strongly indicate that PE funds have strong incentive to use herding strategy to enhance fund performance and minimise its risk exposure. Therefore, the incentive to herd following the benchmark is stronger than the incentive to herd simultaneously.

[Table 5 About Here]

4.4. Persistence in herding

The results reported so far suggest that herding behaviour is likely to be attractive to buyout fund managers over time when we compare the sequential funds of the same buyout firm. For example, Koch (2017) found persistence in the herding behaviours of mutual fund managers, arguing that when skilled mutual fund managers trade together, they are likely to exhibit significant herding behaviours in subsequent periods. Typically, buyout fund managers are specialised by sector and are also likely to be skilled; hence, investigating whether their herding behaviour is also persistent in subsequent funds is important. Therefore, we examined persistence in herding behaviour over subsequent funds, the results of which are reported in Table 6. The dependent variables in the table are the herding measures of the current fund, while the explanatory variables are the herding measures of the same fund manager's previous fund (t – 1). Notably, we control for the fund size in all the reported models. The table shows persistence in herding, as measured by contemporaneous and following herding. Moreover, Models 1 and 2 illustrate that herding behaviour persisted among buyout fund managers who used both the measures of herding. Moreover, the persistence in herding was higher for contemporaneous than for following herding, and the sizes of coefficients for the herding measures in Model 2 and Model 4 were 0.164 and 0.099, respectively. These results indicate that persistence in the herding behaviours is low among the buyout funds. Therefore, herding behaviour is dynamic and is a direct reaction to new information or new trading strategies from the benchmark funds. Overall, the results of Table 6 show that both the forms of herding behaviour are persistent among subsequent funds, which is consistent with the findings on other types of funds such as mutual funds (Koch, 2017).[5]

[Table 6 About Here]

In their study, Kaplan and Schoar (2005) investigated persistence in PE performance and found strong persistence in fund returns across different funds for the same PE firms. Presumably, strong persistence in performance is explained by herding behaviour among the PE funds. To address the question of whether persistence in performance is due to herding behaviour, we examined the performance persistence of PE funds after controlling for herding behaviour. In Model 1 of Table 7, where the dependent variable is the current fund performance as measured by the IRR, and the independent variable is the previous fund performance, it is evident that performance persists among subsequent funds, which is consistent with the findings of Kaplan and Schoar (2005). Moreover, as shown in models 2 and 3, where lagged contemporaneous and following herding measures were included, respectively, the coefficient for the fund performance remains statistically significant. However, from 23.1%, the magnitude of the coefficient decreases to 7.4% in Model 2 and 9% in Model 3. Furthermore, we examined whether herding in the current fund has an equal impact on performance persistence. Hence, in models 4 and 5, we included the contemporaneous and following herding measures of the current fund instead of the lagged herding measures. Additionally, our findings show that the coefficient of fund performance decreased from 23.1% to 5% in the case of the current contemporaneous herding and from 23.2% to 5.1% in the case of following herding. Therefore, the results reported in Table 7

[5] We consider the persistence in herding in Table 6. The herding measures of the current fund are the dependent variables in the regression, while the herding measures of the same PE firm's previous fund (t – 1) serve as the explanatory variables. One concern here is that overlapping time periods across funds could induce some persistence. If such overlaps are important, persistence should decline with the time that elapses between the funds. In unreported results, we test for this possibility by considering only the cases of funds where there is no overlap in the commitment periods over which the herding behaviour is measured, and the results are consistent. Hence, our result suggests that persistence is not influenced by the overlap in time period.

suggest that although fund performance persists across different periods, herding behaviour explains more than 50% of the performance persistence of PE.

[Table 7 About Here]

4.5. Further analyses

After examining the impact of herding behaviour on the performance and risk of all the PE funds, including our benchmark funds, we explored whether our findings were robust after the exclusion of these benchmark funds in our analysis. Our results might be partially driven by the benchmark performance rather than herding behaviour of the other PE funds towards the benchmark. Panel A of Table 8 shows the results related to the contemporaneous herding measure, while Panel B shows the results related to following herding. Model 1 and Model 2 in Panel A show that the impact of contemporaneous herding on the performance remained significant when the performance of the benchmark PE funds was excluded. This evidence is robust in model 3 and 4 that used the following herding measure. Compared with the results in Table 4, the sizes of the coefficients here are relatively smaller in magnitude, yet statistically and economically significant. Overall, the results reported in Table 8 show that herding behaviours have significant impact on the performance, regardless of the inclusion or exclusion of the benchmark PE funds.

[Table 8 About Here]

Table 9 represents the results of a similar analysis related to the risk as measured by fund volatility. Panel A shows the results related to the contemporaneous herding measure, while Panel B shows the results related to the following herding measure. In Panel A, models 1 and 2 show that contemporaneous herding had a negative impact on the risks, controlling for fund characteristics. Similarly, as shown in models 3 and 4 of Panel B, the following herding measure had a negative impact on the risk. Compared with the results reported in Table 5, in Table 9, the size of the coefficients was smaller but remained significant at 1% conventional level. Overall, the results of Table 9 show that the negative impact of herding measures on the risk is not driven by the benchmark funds. It seems that PE funds have an increased incentive to herd due to the possibility of maximising the returns and minimising the risk of their funds.

[Table 9 About Here]

As Table 10 shows, we examined the impact of herding behaviour on the performance by using Public Market Equivalent (PME) instead of IRR. PME is a relative performance measure that can compare a buyout investment to an equivalently timed investment in the relevant public market. Typically, when a PME is greater than 1, investors in a given buyout deal gain more wealth than they would have achieved if they had invested in the public markets. We calculated PME as the ratio of discounted cash inflow to the discounted cash outflow, where the discount rate was the total return in the corresponding stock market. For investments in US portfolio companies, we used the S&P 500 as a proxy for the public market in a manner similar to that of Kaplan and Schoar (2005). For investments outside the US, we used the corresponding local stock market index. Panel A of Table 10 shows the results related to the contemporaneous herding measure, while Panel B shows the results related to the following herding measure. Models 1 and 2 in Panel A show that the impact of contemporaneous herding on the performance by using PME remained statistically and economically significant. This evidence was robust and consistent concerning the use of the following herding measure, as shown in models 3 and 4. Overall, the results reported in Table 10 show that herding behaviours has a significant impact on the performance when PME is used instead of IRR. Hence, the results of Table 4 concerning the impact of herding behaviour on the performance as measured by the IRR are robust.

[Table 10 About Here]

The results reported in Table 5 represent the impact of herding behaviour on the total risk. Although the upside risk is a good risk, the downside risk is a bad risk and a concern for investors. Typically, investors worry about the underperformance rather than overperformance. Hence, investigating the impact of downside risk is more meaningful than investigating the total risk, as it includes both downside as well as upside risk. Panel A in Table 11 shows the impact of contemporaneous herding on downside volatility. As models 1 and 2 show, we found strong evidence supporting that contemporaneous herding leads to lower downside risk when controlled for different fund characteristics. Moreover, the evidence is statistically and economically significant. An increase of 1 in the standard deviation in herding decreased the risk by over 5.5%. However, when controlled for fund characteristics, a unit increase in the standard deviation decreased the risk by 3.3%.

Panel B of Table 11 reports the results of following herding on the downside risk. Models 1 and 2 show that following herding had a negative significant impact on downside risk. Consistent with the results reported in Panel A for contemporaneous herding., Overall, the results of Table 11 show that contemporaneous and following herding have a negative impact on the downside risk exposure of buyout funds. Consistent with the results reported in Table 5, the herding behaviour among the PE funds also decreased the downside risk exposure of the PE funds.

[Table 11 About Here]

Finally, we replicated the results on the sample consisting of US funds only and based on a purely US-based benchmark. To perform this check of robustness, we used the same methodology as before to calculate the herding measures but this time with the sample of US funds only. Then, we analysed the performance and risk. The results are reported in Table 12 and show similar findings as those related to the international sample.

[Table 12 About Here]

5. Conclusions

Among investors, herding occurs in different financial markets frequently. Therefore, we examined the buyout industry, which is characterised by long-term illiquid investments and the need for active involvement in the portfolio companies. In particular, herding towards larger and better established industry players may become valuable for smaller funds 8 that have less investment expertise and may otherwise adopt different risk profiles. Herding behaviour leads to correlated investment choices, which can be either contemporaneous or with a lag. This study explored the presence of both forms of herding on the ultimate fund performance and risk. It was found that industry herding is more common during market contractions (i.e., reduction in the overall capital commitments to the industry) or the deterioration of relevant market conditions. Furthermore, we also found that herding generates higher fund returns and lower risk, suggesting better investment decisions for funds.

A question that arises for further research concerns the skills which enable a PE fund manager to take advantage of herding to, in particular, be able to herd contemporaneously. While we find benefits in herding towards largest industry players, this is likely to require specific skills and experience, as otherwise, any fund may find it profitable to do so. As more information is necessary to offer a detailed analysis of this question, we leave this matter open for future research.

References

Ang, A., Chen, J., Xing, Y., 2006. Downside risk. Review of Financial Studies 19, 1191–239.

Banerjee, A.V., 1992. A simple model of herd behavior. *Quarterly Journal of Economics* 107 (3), 797–817.

Bernile, G., Cumming, D., Lyandres, E., 2007. The size of venture capital private equity fund portfolios. *Journal of Corporate Finance* 13, 564–90.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural changes as information cascades. *Journal of Political Economy* 100 (5), 992–1026.

Bikhchandani, S., Sharma, S., 2000. Herd behavior in financial market: A review. International Monetary Fund Working Paper Series WP/00/48.

Buchner, A., Mohamed, A., Schwienbacher, A., 2017. Diversification, risk and returns in venture capital. *Journal of Business Venturing* 32 (5), 519–35.

Chevalier, J., Ellison, G., 1999. Career concerns of mutual fund managers. *Quarterly Journal of Economics* 114 (2), 389–432.

Chung, J-W., Sensoy, B.A., Stern, L., Weisbach, M.S., 2012. Pay for performance from future fund flows: The case of private equity. *Review of Financial Studies* 25 (11), 3259–304.

Cochrane, J.H., 2005. The risk and return of venture capital. *Journal of Financial Economics* 75, 3–52.

Cressy, R., Munari, F., Malipiero, A., 2007. Playing to their strengths? Evidence that specialization in the private equity industry confers competitive advantage. *Journal of Corporate Finance* 13 (4), 647–69.

Cumming, D., 2008. Contracts and exits in venture capital finance. *Review of Financial Studies* 21 (5), 1947–82.

Cumming, D., Dai, N., Haß, L.H., Schweizer, D., 2012. Regulatory induced performance persistence: Evidence from hedge funds. *Journal of Corporate Finance* 18 (5), 1005–22.

Cumming, D., Schmidt, D., Walz, U., 2010. Legality and venture capital governance around of the world. *Journal of Business Venturing* 25, 54–72.

Cumming, D., Walz, W., 2010. Private equity returns and disclosure around the world. *Journal of International Business Studies* 41, 727–54.

Fama, E., 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance* 25, 383–417.

Franzoni, F., Nowak, E., Phalippou, L., 2012. Private equity performance and liquidity risk. *Journal of Finance* 67, 2341–73.

Giot, P., Hege, U., Schwienbacher, A. 2014. Are novice private equity funds risk-takers? Evidence from a comparison with established funds. *Journal of Corporate Finance* 27, 55–71.

Gompers, P., Lerner, J., 2000. Money chasing deals? The impact of fund inflows on private equity valuation. *Journal of Financial Economics* 55, 281–325.

Grinblatt, M., Titman, S., Wermers, R., 1995. Momentum investment strategies, portfolio performance and herding: A study of mutual fund behavior. *American Economic Review* 85, 1088–105.

Gümbel, A., 2005. Herding in delegated portfolio management: When is comparative performance information desirable? *European Economic Review* 49 (3), 599–626.

Harford, J., Stanfield, J., Zhang, F., 2015. What does an LBO signal for the target's industry? Working paper. Available at:
https://pdfs.semanticscholar.org/0e7f/fe62b2bf02a12bc3859deb9bc007208ae7ed.pdf

Harris, R.S., Jenkinson, T., Kaplan, S., 2014. Private equity performance: What do we Know? *Journal of Finance* 69 (5), 1851–82.

Humphery-Jenner, M., 2012. Private equity fund size, investment size, and value creation. *Review of Finance* 16, 799–835.

Kanniainen, V., Keuschnigg, Ch., 2003. The optimal portfolio of start-up firms in venture capital finance. *Journal of Corporate Finance* 9, 521–34.

Kaplan, S., Schoar, A., 2005. Private equity performance: Returns, persistence and capital flows. *Journal of Finance* 60, 1791–1823.

Kaplan, S., Stromberg, P., 2009. Leveraged buyouts and private equity. *Journal of Economic Perspectives* 23, 121–46.

Knill, A., 2009. Should venture capitalists put all their eggs in one basket? Diversification versus pure-play strategies in venture capital. *Financial Management* 38, 441–86.

Koch, A., 2017. Herd behavior and mutual fund performance. *Management Science* 63 (11), 3849–73.

Korteweg, A.G., Sorensen, M., 2014. Skill and luck in private equity performance. Rock Center for Corporate Governance Working Paper Series No. 179.

Krohmer, P., Lauterbach, R., Calanog, V., 2009. The bright and dark side of staging: investment performance and the varying motivations of private equity firms. *Journal of Banking and Finance* 33, 1597–1609.

Kremer, S., Nautz, D., 2013. Causes and consequences of short-term institutional herding. *Journal of Banking and Finance* 37, 1676–86.

Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. *Journal of Financial Economics* 32, 23–43.

Markowitz, H., 1991. Portfolio Selection: Efficient Diversification of Investments, second ed. Basil Blackwell, Cambridge, MA.

Maug, E., Naik, N., 2011. Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation. *Quarterly Journal of Finance* 1 (2), 265–92.

Shawky, H.A., Dai, N., Cumming, D.J., 2012. Diversification in the hedge fund industry. *Journal of Corporate Finance* 18 (1), Pages 166–78.

Tobin, J., 1958. Liquidity preference as behavior towards risk. Review of Economic Statistics 25, 65–86.

Welsh, I., 1992. Sequential sales, learning and cascades. *Journal of Finance* 47, 695-732.

Wermers, R., 1999. Mutual fund herding and the impact of stock prices. *Journal of Finance* 54 (2), 581–622.

Table 1 Descriptive Statistics.

This table shows descriptive statistics (mean, median, standard deviation, minimum, and maximum) for the variables of our study. Apart from herding measures, which have been explained in the section on methodology, the terms appearing in the table are defined as follows: *IRR* is the annualised internal rate of return of the fund. *Fund volatility* is the annualized volatility of the fund. *Portfolio company* is the number of investments made by the fund. *Sequence* is the sequence number. Fund families raise one fund at a time, hence the first fund raised by a given fund family is assigned a sequence number of 1, the second fund a sequence number of 2, and so on. *Ln fund size* is the natural logarithm of the fund size in USD. *Syndication (fraction)* is the fraction of the deals of the syndicated fund. *Ln capital committed* is the natural logarithm of the total capital committed to buyout funds worldwide (in USD million) in the vintage year of the fund (source: PREQIN Private Equity Analyst). *Number of deals* is the number of all the PE-backed deals in the US in the vintage year of the fund (source: Thomson Reuters). *Number of IPOs* is the number of the PE-backed IPOs in the US in the vintage year of the fund (source: Thomson Reuters).

Variables	Mean	Median	S.D.	Min	Max
Contemporaneous herding	0.042	0.052	0.160	-0.798	0.775
Following herding	0.010	0.009	0.137	-0.551	0.624
IRR	0.313	0.270	0.219	-0.211	1.623
Fund volatility	0.758	0.526	0.687	0.000	3.010
Portfolio company	17.076	13.211	18.230	1.000	216.000
Sequence	7.321	3.098	10.051	1.000	175.000
Ln fund size	25.485	25.169	1.529	10.536	29.916
Syndication (fraction)	0.595	0.480	0.315	0.010	1.000
Ln capital committed	10.565	10.612	1.194	3.506	12.040
Number of deals	613.121	621.000	259.394	10.000	1102.000
Number of IPOs	157.379	148.000	82.573	1.000	331.000
No. of obs.	878				

Table 2: Correlation Matrix

This table shows the correlation matrix of all the variables used in the analysis. All the variables are defined in Table 1. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Contemporaneous herding	(1)	1										
Following herding	(2)	0.1271**	1									
IRR	(3)	0.0803	0.0164	1								
Fund volatility	(4)	-0.0324	-0.0259	0.4023***	1							
Portfolio company	(5)	0.0746	-0.0276	0.0389	0.1123**	1						
Sequence	(6)	0.0239	-0.0354	-0.0014	-0.0677	0.1685***	1					
Ln fund size	(7)	0.1245**	0.0488	-0.1438**	-0.0663	-0.0261	0.3499***	1				
Syndication (fraction)	(8)	-0.0279	0.064	0.0097	0.0934	0.0748	-0.1164**	-0.1315**	1			
Ln capital committed	(9)	-0.101	-0.0742	-0.1945**	-0.1381**	-0.3710***	0.1509**	0.3712***	-0.2069***	1		
Number of deals	(10)	-0.063	-0.1295**	-0.1570**	-0.1484**	-0.422***	0.1771**	0.3318***	-0.2458***	0.8724***	1	
Number of IPOs	(11)	-0.0586	-0.0854	-0.1311**	0.0236	0.1105*	-0.1199**	-0.0511	0.1179**	0.0619	0.1093*	1

Table 3 Determinants of Herding

This table shows the determinants of following (Panel A) and contemporaneous (Panel B) herding using fund characteristics and market conditions. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Panel A: Contemporaneous herding	***Model 1***	***Model 2***	***Model 3***
Ln capital committed	-0.0541***		
	(0.000)		
Number of deals		-0.0040***	
		(0.000)	
Number of IPOs			-0.0661***
			(0.000)
Ln fund size	0.0104*	0.0112***	0.0109***
	(0.054)	(0.000)	(0.000)
Ln sequence	0.0147**	0.0157***	0.0126***
	(0.024)	(0.000)	(0.000)
Syndication (fraction)	-0.0093	-0.0169***	-0.0184***
	(0.289)	(0.000)	(0.000)
No. of obs.	878	878	878
Adjusted R-square	0.245	0.221	0.211

Table 3 continues

Panel B: Following herding	***Model 1***	***Model 2***	***Model 3***
Ln capital committed	-0.0093		
	(0.837)		
Number of deals		-0.0043***	
		(0.000)	
Number of IPOs			-0.0473***
			(0.000)
Ln fund size	0.0055	0.0226***	-0.0013
	(0.867)	(0.000)	(0.841)
Ln sequence	-0.0105***	-0.0166***	-0.0119***
	(0.000)	(0.000)	(0.000)
Syndication (fraction)	-0.0217***	-0.0212***	-0.0179***
	(0.000)	(0.000)	(0.000)
No. of obs.	878	878	878
Adjusted R-square	0.231	0.217	0.209

Table 4: Impact of Herding on Performance

This table shows the impact of the different herding measures on the performance measured by the fund's IRR. Panel A shows the results for the contemporaneous herding measure, and Panel B for following herding measure. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: Contemporaneous herding		***Panel B: Following herding***	
Variables	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Contemporaneous herding	0.1820**	0.1720***		
	(0.017)	(0.000)		
Following herding			0.4210***	0.3430***
			(0.000)	(0.000)
Portfolio company		-0.0590**		-0.0102**
		(0.021)		(0.041)
Ln sequence		0.0133***		0.0154***
		(0.001)		(0.000)
Ln fund size		0.0179**		0.0213***
		(0.021)		(0.000)
Syndication (fraction)		0.0407***		0.0577***
		(0.000)		(0.000)
No. of obs.	878	878	878	878
Adjusted R-square	0.251	0.236	0.261	0.237

Table 5: Impact of Herding on Risk

This table shows the impact of the different herding measures on risk measured by the fund's volatility. Panel A shows the impact of contemporaneous herding measure, and Panel B shows the impact of the following herding measure. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: Contemporaneous herding		***Panel B: Following herding***	
Variables	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Contemporaneous herding	-0.6870***	-0.1420***		
	(0.000)	(0.000)		
Following herding			-0.8540***	-0.6521***
			(0.000)	(0.000)
Portfolio company		0.0164**		0.0162**
		(0.033)		(0.039)
Ln sequence		0.0188***		0.0209***
		(0.000)		(0.000)
Ln fund size		0.0106**		0.0102**
		(0.021)		(0.019)
Syndication (fraction)		0.1220***		0.1100***
		(0.000)		(0.000)
No. of obs.	878	878	878	878
Adjusted R-square	0.291	0.301	0.310	0.322

Table 6: Persistence in Herding

This table reports the persistence in herding as measured by contemporaneous and following herding measures. The dependent variables in the regression are the herding measures of the current fund, while the explanatory variables are the herding measures of the previous fund (t – 1) of the same PE firm. models 1 and 2 show the results for contemporaneous herding measure as the dependent variable, while models 3 and 4 show the results for the following herding measure as the dependent variable. All the variables are defined in Table 1. The variable *Fund size* is used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Contemporaneous herding (t–1)	0.2551***	0.1640***		
	(0.000)	(0.000)		
Following herding (t–1)			0.1950***	0.0998***
			(0.000)	(0.000)
Ln fund size		0.0110***		-0.0576***
		(0.000)		(0.000)
No. of obs.	789	789	789	789
Adjusted R-square	0.221	0.412	0.366	0.401

Table 7: Impact of Herding on Performance Persistence

This table shows the impact of the different herding measures on performance persistence. The dependent variable is the IRR at t_0. Model 1 shows the results concerning persistence, while Model 2 shows the results after controlling for contemporaneous herding at lag one, and Model 3 shows the results after controlling for following herding measures at lag one. Meanwhile, Model 4 and Model 5 show the impact of herding measures at t_0. All the variables are defined in Table 1. The variable *Fund size* is used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
IRR (t–1)	0.2310***	0.0740***	0.0905***	0.0506***	0.0515***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Contemporaneous herding (t–1)		0.1350***			
		(0.000)			
Following herding (t–1)			0.0549***		
			(0.000)		
Contemporaneous herding				0.0716***	
				(0.000)	
Following herding					0.0344***
					(0.000)
Ln fund size		-0.0137*	-0.0143*	-0.0189*	-0.0116***
		(0.087)	(0.066)	(0.076)	(0.081)
No. of obs.	789	789	789	789	789
Adjusted R-square	0.226	0.361	0.337	0.331	0.303

Table 8: Impact of Herding on Performance (excluding benchmark funds)

This table shows the impact of the different herding measures on the performance measured by the fund's IRR excluding the benchmark. Panel A shows the results for the contemporaneous herding measure, and Panel B shows the results for the following herding measure. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: Contemporaneous herding		***Panel B: Following herding***	
Variables	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Contemporaneous herding	0.1570***	0.1278***		
	(0.000)	(0.000)		
Following herding			0.2906***	0.2017***
			(0.000)	(0.000)
Portfolio company		-0.0119**		-0.0132**
		(0.031)		(0.020)
Ln sequence		0.0192***		0.0157***
		(0.000)		(0.008)
Ln fund size		0.0279**		0.0405**
		(0.041)		(0.021)
Syndication (fraction)		0.0106***		0.0155*
		(0.000)		(0.091)
No. of obs.	659	659	659	659
Adjusted R-square	0.243	0.216	0.251	0.211

Table 9: Impact of Herding on Risk (excluding benchmark funds)

This table shows the impact of the different herding measures on the risk measured by the fund's volatility excluding the benchmark. Panel A shows the impact of contemporaneous herding measure, and Panel B shows the impact of the following herding measure. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: Contemporaneous herding		***Panel B: Following herding***	
Variables	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Contemporaneous herding	-0.2801***	-0.1060***		
	(0.000)	(0.000)		
Following herding			-0.4301***	-0.2780***
			(0.000)	(0.000)
Portfolio company		0.0592**		0.0646**
		(0.029)		(0.031)
Ln sequence		0.0315***		0.0423***
		(0.000)		(0.000)
Ln fund size		0.0618**		0.0591**
		(0.019)		(0.023)
Syndication (fraction)		0.2300***		0.1700***
		(0.000)		(0.000)
No. of obs.	659	659	659	659
Adjusted R-square	0.264	0.281	0.291	0.301

Table 10: Impact of Herding on Performance (PME)

This table shows the impact of the different herding measures on the performance measured by the fund's Public Market Equivalent (PME). Panel A shows the results for the contemporaneous herding measure, and Panel B shows the results for following herding measure. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: Contemporaneous herding		***Panel B: Following herding***	
Variables	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Contemporaneous herding	0.3440***	0.2188**		
	(0.000)	(0.031)		
Following herding			0.4710***	0.3620***
			(0.000)	(0.000)
Portfolio company		-0.0171**		-0.0183**
		(0.024)		(0.031)
Ln sequence		0.1850***		0.1270***
		(0.000)		(0.000)
Ln fund size		0.0255***		0.0175**
		(0.000)		(0.037)
Syndication (fraction)		0.0101*		0.0236***
		(0.053)		(0.000)
No. of obs.	878	878	878	878
Adjusted R-square	0.212	0.194	0.231	0.01

Table 11: Impact of Herding on Risk (downside volatility)

This table shows the impact of the different herding measures on the downside risk measured by the fund's downside volatility. Panel A shows the impact of contemporaneous herding measure, and Panel B shows the impact of the following herding measure. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: Contemporaneous herding		***Panel B: Following herding***	
Variables	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Contemporaneous herding	-0.0555***	-0.0330***		
	(0.000)	(0.000)		
Following herding			-0.1190***	-0.0397***
			(0.000)	(0.000)
Portfolio company		0.0144***		0.0143***
		(0.000)		(0.000)
Ln sequence		0.0112**		0.0126**
		(0.021)		(0.018)
Ln fund size		0.0026*		0.0037*
		(0.077)		(0.081)
Syndication (fraction)		0.0578**		0.0527**
		(0.029)		(0.031)
No. of obs.	878	878	878	878
Adjusted R-square	0.284	0.293	0.298	0.305

Table 12: Impact of Herding on Performance and Risk (sample of US funds only)

This table shows the impact of the different herding measures on the performance and risk for the subsample of US funds. Panel A shows the results for the performance, and Panel B shows for risk measured by the fund's IRR and volatility, respectively. All the variables are defined in Table 1. The variables *Fund size* and *Sequence* are used in the natural log. The values in parentheses are p-values, which are based on heteroskedasticity-corrected standard errors. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Panel A: Performance		***Panel B: Risk***	
Variables	***Dep. Var.: IRR***	***Dep. Var.: IRR***	***Dep. Var.: Volatility***	***Dep. Var.: Volatility***
Contemporaneous herding	0.0697**		-0.1305**	
	(0.016)		(0.022)	
Following herding		0.1846**		-0.2331***
		(0.010)		(0.000)
Portfolio company	-0.0027**	-0.0033*	0.0125**	0.0155**
	(0.031)	(0.053)	(0.041)	(0.034)
Ln sequence	0.0164**	0.0198**	0.0485**	0.0690**
	(0.031)	(0.022)	(0.031)	(0.041)
Ln fund size	0.017**	0.0138**	0.0018**	0.0013**
	(0.016)	(0.031)	(0.041)	(0.031)
Syndication (fraction)	0.0153**	0.0204**	0.1132**	0.1165**
	(0.018)	(0.031)	(0.041)	(0.029)
No. of obs.	363	363	363	363
Adjusted R-square	0.166	0.177	0.191	0.201