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Private Equity Fund Valuation Management During Fundraising

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Abstract

I investigate whether and how private equity fund managers (GPs) inflate their interim fund valuations (net asset values, or NAVs) during fundraising periods. Specifically, I study the extent to which the GPs inflate NAVs by managing valuation assumptions (e.g., valuation multiples), influencing the financial metrics (e.g., EBITDA and sales) reported by the private firms in their portfolios, or both. Using a sample of buyout funds and their portfolio firms in Europe, I find that funds managed by low reputation GPs show more dramatic forms of NAV inflation by managing upward not only valuation multiples but also portfolio firm earnings. The results are robust to a number of alternative explanations. Low reputation GPs that employ some form of earnings management show success in fundraising. Overall, I illustrate the mechanisms behind inflated fund valuations during fundraising periods and provide evidence supporting the argument that low reputation GPs are more likely to manipulate NAVs than time fundraising periods.

JEL codes: G10; G20; G23; G24; M4; M42
Keywords: Private equity; institutional investors; valuation multiples; earnings management; private firms

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1 Introduction

I study whether and how private equity (PE) fund investors (hereafter general partners or GPs) manipulate their fund performance during fundraising periods. Recent studies (i) have found abnormally high PE fund valuations during fundraising periods and (ii) have debated (but have not settled) whether these valuations reflect manipulating the existing funds' values (hereafter net asset values or NAVs) or timing their fundraising activities during periods of peak performance (e.g., Barber and Yasuda, 2017; Brown, Gredil, and Kaplan, 2019; Hüther, Forthcoming).[1] As I elaborate below, a fund's NAV can be decomposed into (i) valuation multiples (hereafter multiples or market multiples) and (ii) earnings of the portfolio firms. I examine the components of the NAVs and provide evidence that funds managed by low reputation GPs show inflated valuation multiples and inflated financial performance of their investments during fundraising, which is consistent with the manipulation hypothesis.

To study whether and how GPs inflate their current fund performance during fundraising, I exploit the fact that a fund's NAV consists of valuation multiples and portfolio firm earnings. (See Section 2.2 and Figure 2 for a numerical example of how NAV is calculated using the multiples approach.) Specifically, because many of the PE investments are private and do not have quoted market prices, GPs provide fair values using a number of valuation techniques. One of the most common methods is to apply multiples to their portfolio firm earnings, such as EBITDA or sales (IPEV, 2018).[2] Supporting this recommendation, a survey by Grant Thornton (2015) of GPs shows that 87.2% of the respondents use the multiples method to value their investments. The underlying assumption throughout the paper is that PE funds report their NAVs using this method. Therefore, to increase NAVs through this method, GPs can either choose to apply higher multiples or to use manage the earnings of their

[1]For example, Barber and Yasuda (2017) show results consistent with the market timing hypothesis, whereas Brown et al. (2019) find evidence consistent with the manipulation hypothesis, specifically for under-performing funds. Overall, the literature is inconclusive on whether PE funds are timing their fundraising or manipulating fund valuations.

[2]Indeed, prior studies demonstrate that the NAVs of PE funds are associated with both the fundamentals of their firms in their portfolios (Ferreira, Kräussl, Landsman, Borysoff, and Pope, 2019) and future cash flows (Jenkinson, Landsman, Rountree, and Soonawalla, 2020).

investments (i.e., actions that temporarily increase firm earnings, but would later reverse; these are not illegal. See Section 4.2 for a detailed definition.)

I predict that GPs use aggressive multiples, inflate portfolio firm earnings, or both to manipulate their NAVs during fundraising periods. There are multiple reasons for this prediction. First, theory provides a rationale for performance manipulation for at least a subset of PE funds (e.g., Brown et al., 2019; Chung, Sensoy, Stern, and Weisbach, 2012). The intuition of these models is that, similar to the results from Stein (1989), low reputation GPs are 'forced' to manage their current fund valuations because without them, low reputation GPs face even lower chance of raising a subsequent fund. Second, GPs have the ability to inflate both multiples and portfolio firm earnings. Inflating valuation multiples is possible because NAVs are calculated using GP's discretionary assumptions and inputs (Phalippou and Gottschalg, 2009). Indeed, survey evidence (Grant Thornton, 2015) suggests that approximately two-thirds of GPs use their internal calculations to report NAVs. GPs can also manage portfolio firm earnings because they exert significant operational influence on their investments by (i) investing majority equity stakes in their portfolio firms, (ii) controlling the boards, and (iii) appointing managers of the portfolio firms (Acharya, Kehoe, and Reyner, 2009).

Yet there are also reasons why GPs might not manage their valuations using the two strategies mentioned above. First, LPs and regulators try to detect NAV overvaluation. Second, GPs may use different ways to inflate their performance, such as exiting firms prematurely or using different valuation methods. Finally, aggressive inflation of portfolio firm earnings (by using some types of earnings management) can hurt long-term portfolio firm fundamentals, and therefore reduce the ultimate exit value for the GPs.

A key challenge in testing my hypotheses is that doing so requires financial statement information of individual portfolio firms, which are private and do not usually disclose financial statements in the United States. To address this challenge, I use a sample of European private firms and buyout funds[3] that invest in them. An important advantage of using the European setting is that I can observe private firm financial statements as many European countries require limited liability firms above a certain size threshold to disclose financial statement information. Furthermore, Europe is the second-largest PE market in the world (McKinsey, 2021). To construct my sample, I match fund-level valuation data from Preqin with portfolio firm financial statement data from Amadeus. The sample consists of 410 buyout funds and 1,838 portfolio firms.

Testing my main hypotheses requires two steps. First, following the design from Barber and Yasuda (2017), I partition the samples by GP reputation because prior studies (e.g., Barber and Yasuda, 2017; Brown et al., 2019) show that low reputation/low performing funds have larger incentives to manipulate fund NAVs than do high reputation GPs. The intuition behind these findings is that the lack of reputation forces these GPs to rely much more on their interim fund performance for fundraising. Second, I compare the valuation metrics (either valuation multiple or portfolio firm earnings) of the funds managed by low reputation GPs to those managed by high reputation GPs.

To test whether *valuation multiples* increase during fundraising, for each low and high reputation GP sample, I regress the ratio of NAV/EBITDA (and NAV/Sales) on a dummy variable that indicates periods with or without fundraising. These ratios serve as proxies for valuation multiples. The key distinguishing feature of my research design from extant research is that I focus on the valuation multiples used, instead of the aggregate NAV of the fund. To control for time-invariant fund-level characteristics and time attributes, I add fund fixed effects and calendar year-quarter fixed effects, respectively.

To investigate whether *portfolio firm earnings* abnormally increase during fundraising, I transition to portfolio firm data and test whether PE investments owned by low versus high

[3] I use a sample of buyout funds because the effect of manipulation is thought to be greater for these funds (e.g., Barber and Yasuda, 2017; Hüther, Forthcoming), and because these funds invest in more mature firms. Therefore financial statement information is viewed to be more informative than venture capital (VC) fund investments. I follow Preqin's definition of buyout funds, following prior studies (e.g., Barber and Yasuda, 2017).

reputation GPs manipulate earnings during fundraising. Specifically, similar to the fund-level analysis, I regress portfolio firm earnings management (EM) on the fundraising indicator for funds with a low versus high reputation. To capture EM, I use performance-matched accruals earnings management (AEM) and real earnings management (REM). AEM is defined as managers shifting accruals to temporarily increase firm earnings; REM is defined as managers taking real actions (e.g., building up excess inventory to reduce cost of goods sold, drastically reducing expenses that could have long-term payoffs, such as R&D expenses) to also increase earnings in the short-term. I focus on measures of EM instead of conventional measures of financial performance (e.g., ROA or sales growth) variables, because EM proxies provide clearer evidence of aggressiveness than do financial performance metrics. To avoid measurement errors of EM variables noted in Chen, Hribar, and Melessa (2018), I include both first-step and second-step regressors in the portfolio firm-level regressions, following their recommendations. For the portfolio firm-level tests, I additionally add portfolio firm fixed effects and portfolio firm country-industry-year fixed effects to capture time-invariant portfolio company characteristics and time-varying country and industry attributes, respectively.

An important alternative interpretation of my findings is that higher valuation multiples or EM could be due to the GPs *timing* fundraising periods (Barber and Yasuda, 2017). To rule out this interpretation, for both tests, I conduct entropy balancing and re-weight nonfundraising quarters to have similar motives to time fundraising with fundraising quarters. Specifically, I require nonfundraising quarters to have similar first and second moments in terms of fund age, valuation, fund size, distribution, and fundraising year, and re-estimate the main regressions. By re-weighting nonfundraising fund-quarters,[4] the assumption is that even the nonfundraising quarters are somewhat motivated to time fundraising. Ultimately, I can mitigate the alternative hypothesis that GPs are timing their fundraising periods at

[4]These fund-quarters should have a similar fundraising timeline and motivation with fundraising ones because of similar PE fundraising market conditions (by matching with calendar year-quarter) and similar fund age (since funds have a fixed life).

their performance peak.

The regression results suggest a significant increase in valuation multiples for funds with low reputation GPs but not for high reputation GPs. In economic terms, EBITDA and sales multiples increase by 18.2% and 22.7%, respectively, compared to nonfundraising periods. Entropy-balanced samples also demonstrate similar findings. In contrast, high reputation GPs *reduce* their valuation multiples during the same period, which is consistent with Brown et al. (2019) that show conservative performance for these GPs. Seemingly unrelated regression (SUR) tests indicate that the difference between the multiples of low and high reputation GPs are statistically significant. Collectively, the results are consistent with my hypotheses and prior findings that low reputation GPs have stronger incentives to overstate their NAVs via an increase in valuation multiples.

Next, the results of the EM regressions indicate that portfolio firms of low reputation buyout GPs engage in both AEM and REM to inflate their earnings. Specifically, holdings of low reputation buyout GPs exhibit higher abnormal accruals (3.8% of portfolio firm assets), abnormal production costs (14.3% of portfolio firm assets),[5] which are consistent with my findings at the fund level. Using entropy-balanced samples exhibit statistically stronger results than the main sample. On the contrary, investments from high reputation GPs do not show (if anything, reduces EM) any evidence of EM during their fundraising. SUR tests confirm that the coefficients are substantially different between low and high reputation GPs.

Next, I conduct a falsification test using a sample of VC transactions and buyout transactions with more than two investors. Because there are multiple investors involved in a portfolio firm, I anticipate that one investor does not have enough control to influence portfolio firm to engage in EM, even if the GP is motivated to influence portfolio firms to do so. I do not find any meaningful results, consistent with the argument that portfolio firms with multiple investors lower the amount of influence made by one investor.

[5]While the coefficient is larger compared to previous studies (approximately 5% point in Roychowdhury (2006) and in Gunny (2010)), my sample consists of European private firms (which are smaller in general compared to US public firms) and therefore the magnitude can be larger.

I present additional tests to triangulate my results and address different explanations of my findings. The first is that stronger abnormal earnings performance is merely a consequence of GPs' improvements in their investments' operational efficiency (e.g., Bernstein and Sheen, 2016; Cohn, Mills, and Towery, 2014; Guo, Hotchkiss, and Song, 2011). To address this interpretation, I test the effects of PE ownership during non-fundraising periods. More specifically, I test whether GP ownership is associated with EM by comparing portfolio firm-years with and without low reputation GP ownership and find no significant relation with EM. Second, I find that both valuation multiples and EM proxies reverse post fundraising, reducing the concern that my results are capturing an increase in fund/portfolio firm efficiency, rather than capturing manipulations by the GPs. By showing the reversals in multiples and in EM, I also verify that the findings are not attributable to reduced GP attention to their investments, a possibility raised by Brown et al. (2019).[6] Third, I explore the possibility that the results may be driven by fundraising periods coinciding with portfolio firms' exit timing. GPs may be managing the performance of their investments to maximize the exit values, rather than to raise funds. To alleviate this concern, I remove portfolio firm-years one or two calendar years before their exits and re-estimate my analyses. The results remain unchanged.

In my final set of tests, I examine the consequences of the overstated valuation multiples and the financial performance of the underlying investments. While previous literature (e.g., Barber and Yasuda, 2017; Brown et al., 2019) has documented NAV management strategies to be unsuccessful, strategies executed at the portfolio firm level could potentially increase the chances of low reputation GPs to succeed in fundraising. I test and find that low reputation GPs that use some forms of EM (specifically AEM) are associated with successful fundraising, which is in contrast to previous findings. On the other hand, while having higher valuation multiples during *nonfundraising* periods is effective for future fundraising, having them during *fundraising* periods is not, consistent with findings that the LPs can look

[6]This is because setting valuation multiples should consume far less time than monitoring fund investments.

through these efforts (Brown et al., 2019).

This paper complements the debate *whether* GPs manipulate their performance by demonstrating *how* they achieve manipulation during fundraising (compared to previous studies that only document *whether* they manipulate their valuations). My evidence supports the manipulation hypothesis by showing that GPs can inflate valuation multiples and the financial performance of their portfolio firms to increase NAVs. In addition, I demonstrate that some forms of manipulation can increase the GPs' chances of successful fundraising, which is in contrast to results from Brown et al. (2019) who find GPs' efforts to manipulate fund NAVs are largely unsuccessful. By doing so, this study extends the PE literature with respect to the fund reporting behavior during fundraising (e.g., Barber and Yasuda, 2017; Brown et al., 2019; Chakraborty and Ewens, 2018; Gompers, 1996; Hüther, Forthcoming; Jenkinson, Sousa, and Stucke, 2013).

My findings also contribute to the literature on (i) valuation of illiquid (Level III) assets and (ii) transparency of private firms. Regarding the valuation of illiquid assets, most of the research in this area has focused on whether the financial performance of portfolio firms matter for Level III asset valuation (e.g., Altamuro and Zhang, 2013; Ferreira et al., 2019; Jenkinson et al., 2020; Lawrence, Siriviriyakul, and Sloan, 2016) and the cross-sectional determinants of its valuation accuracy (e.g., Berfeld, 2022). The contribution of this paper is to introduce valuation multiples as a potential determinant of NAVs and managerial motives (fundraising) and GP reputation as novel sources of determinants of valuation accuracy. The findings have implications not only for academics but also for the regulators of the PE industry, who are increasingly interested in this subject (Brown, Carman, and Giaimo, 2018).

With respect to the literature on transparency of private firms, I complement the literature in three ways. First, by focusing on the effect of PE investors on the EM of their portfolio firms, I demonstrate a case where long-term institutional shareholders induce EM by portfolio firms because of their short-term incentives during fundraising periods. Past studies (e.g., Agarwal, Vashishtha, and Venkatachalam, 2018; Bushee, 1998; Katz, 2009; Lisowsky and Minnis, 2020; Zang, 2012) find that, while short-term or transient investors induce EM, long-term investors suppress it. In this paper, I provide a case where long-term institutional owners can also prompt EM when these investors face short-term incentives.[7] Second, in a PE fund setting, I show that fund managers (i.e., GPs) can inflate *valuation multiples* in addition to managing earnings at the portfolio firm level. This is unique compared to public firm settings because public firm (fund) managers are unable to manipulate the multiples. Finally, these findings contribute to the understanding of EM in private firms, which is an integral part of the economy and have different ownership structures.[8]

The paper is organized as follows. Section 2 provides institutional details on PE fundraising. Section 3 describes my data and sample selection process. Section 4 presents my research design. Section 5 discusses the findings. Section 6 concludes.

2 Institutional background

2.1 The structure and the life-cycle of PE funds

PE funds are mostly structured as limited partnerships and are typically closed-end, which means that, once a GP closes the fund (i.e., declares fundraising finished), it will not accept new capital from investors. Figure 1 Panel A depicts a typical PE fund structure. The Fund owns a set of portfolio companies. The GP manages the fund and makes the main investment decisions (e.g., which companies to invest in at what price, when to exit the fund's holdings). The GP receives management fees (typically 2% of the NAV) and 20% of the profit earned. Limited Partners (navy triangle) commit capital to the fund but have limited rights to interfere with investment decisions made by the GP (Lerner and Schoar, 2004). They are often sophisticated investors, such as pension funds, endowments, and high

[7] See Roychowdhury, Shroff, and Verdi (2019) for a review on this subject.

[8] For instance, Invest Europe (2021) report that PE-backed firms comprised approximately 4.3% of the European workforce as of 2019.

net worth individuals (Da Rin and Phalippou, 2017).

A fund normally has a life of approximately 10 to 12 years, with an option to extend its life for two to three additional years. Figure 1 Panel B presents a simplified timeline of a typical fund. For the first five to six years after the fund inception, the GP searches for target firms to invest in (investment phase). As the fund completes its investment transactions, the GP monitors, manages, and then seeks to divest from the portfolio firms (divestment phase); this phase generally takes three to seven years, but the length of this phase can vary according to market conditions (Gompers, Gornall, Kaplan, and Strebulaev, 2020; Gompers, Kaplan, and Mukharlyamov, 2016). Before the fund expires, GPs seek to raise subsequent funds and undergo a marketing phase (i.e., fundraising period) for about one year. This period can begin as early as three to four years after their fundraising initiation (Metrick and Yasuda, 2010).

For the GP's ability to raise subsequent funds, the performance of the GP's existing funds is important. To window-dress performance, GPs can attempt to either manipulate/inflate fund valuations or at least time their fundraising periods at their existing funds' peak performance. For instance, Brown et al. (2019) and Jenkinson et al. (2013) show that at least of a subset of PE funds seem to have manipulated returns during fundraising. In a VC setting, Chakraborty and Ewens (2018) similarly show that portfolio firm write-offs double post fundraising, which is consistent with the manipulation hypothesis. On the other hand, Barber and Yasuda (2017) posit that GPs time their fundraising periods at their existing funds' performance peak.

2.2 PE fund valuation

How are PE funds valued? International Private Equity and Venture Capital Valuation Guidelines (IPEV) issues valuation guidelines periodically (most recently in 2018), and many funds follow these guidelines.[9] To value firms in the portfolios of funds (most of these firms

[9]For example, the IPEV board reports that more than 20 national PE associations (including in the United States, Europe, and China) endorse the guidelines.

are private), IPEV (2018) suggests using fair values (as opposed to valuing the firms at cost). Specifically, among an array of fair value estimation methods (e.g., discounted cash flow, income approach, and replacement cost approach), IPEV shows the valuation multiple approach (i.e., using market-based valuation multiples, such as EV/EBITDA or price/sales multiples) as one of the most common and widespread valuation techniques. A survey of the GPs (Grant Thornton, 2015) also shows that 87.2% of the respondents use the multiple approach, which is the highest among all the listed valuation methods. For each portfolio firm a fund holds, the GP reports portfolio firm earnings and its fair value. Summing the values of the portfolio firms determines the total NAV of a fund. I emphasize that the key identifying assumption throughout this paper is that most NAVs are calculated using the multiples approach. While there are other valuation methods available, I argue this assumption to be reasonable because the method is primarily used across PE practitioners due to its simplicity.

Figure 2 provides a numerical example of how NAVs are calculated. The name of the fund is "CVC European Capital Partners V," a 2008-vintage[10] buyout fund managed by CVC Capital Partners (the GP). The fund invested in portfolio companies, such as Cerved Group, Virgin Active, and Ahlsell, which had EBITDAs of approximately \$150 million, \$50 million, and \$250 million, respectively. Suppose the GP applied EV/EBITDA multiples of 6x, 8x, and 10x for Cerved, Virgin Active, and Ahlsell, respectively. The valuation for each company would be 6x $\times$ \$150m = \$900m (Cerved), 8x $\times$ \$50m = \$400m (Virgin Active), and 10x $\times$ \$250m = \$2.5bn (Ahlesll). The NAV of the fund becomes the sum of these valuations, which is \$900m + \$400m + \$2.5bn = \$3.8 billion.

The valuation process described above requires a significant amount of GP discretion and can lead to abnormal increases in NAV during fundraising. Particularly, there are two non-mutually exclusive ways for the GPs to manage their NAV valuation: (i) valuation multiples and (ii) portfolio firm earnings.

[10] The initiation year of a fund. See Appendix A for a detailed definition.

Figure B1 provides an example of an actual PE fund report.[11] Panel A shows how this GP calculates its portfolio firm value, and Panel B provides an example of a portfolio firm valuation (portfolio firm named FRA). In Panel B, both portfolio firm earnings (EBITDA) and the multiple used to calculate the fair value are reported. Note that the calculated values differ slightly from the valuation of the reported value because the multiple is a weighted average of all multiples across the entire portfolio firms in the fund.

3 Data

A challenge in testing my hypotheses is that I require the financial performance of individual portfolio firms (many of which are private). To address this concern, I use European firms and funds that invest in them (note that these funds are not confined to Europe. See Section 3.4 for a more detailed description), where many countries require both public firms and private limited liability firms over a certain size threshold to disclose their financial statements. Europe is also the second-largest PE market in the world (McKinsey, 2021).

3.1 Data on PE funds and their valuations/transactions

I use two datasets to create my sample. The first dataset is from Preqin, which offers detailed information on GPs, PE fund and fundraising characteristics (e.g., fund name, GP, fund size, fund strategy, and fundraising close date), cash inflow/outflow, valuation (i.e., NAV) of each fund, and a list of buyout transactions to identify the portfolio firms. Preqin sources its data either directly from limited partners and GPs or via Freedom of Information Act (FOIA) requests.[12] In addition, Brown et al. (2015) show that US funds are well covered across all

[11] The report is from Dunedin Enterprise Investment Trust PLC (https://www.dunedinenterprise.com/investors/reports-and-presentations/2018.aspx).

[12] Brown, Harris, Jenkinson, Kaplan, and Robinson (2015) report that, as of 2015, approximately 38% and 59% of the data are from the limited partners and GPs, respectively. A potential concern with high GP data contribution could be that fund valuations may be overstated and therefore bias the multiples upward. However, I conjecture that high reputation PE funds would contribute data more so than low reputation GPs, because of their ample track record and data. This would bias against my results because high reputation GPs would have more conservative NAVs.

vintages, whereas non-US fund coverage dramatically improves from vintages in the 1990s. I do not expect sample selection bias to arise from this issue since my sample begins with 1996 vintages. See Figure IA1 for the distribution of fund vintages; see Brown et al. (2015) for a more extensive review of Preqin's data. Preqin also retrieves information from public filings and annual reports. These sources are commonly used by other commercial datasets (e.g., Pitchbook and Burgiss) to obtain their data. In addition, Harris, Jenkinson, and Kaplan (2014) confirm that the performance data from Preqin is qualitatively similar to other datasets, which reduces the concern that the Preqin dataset may report systematically higher performance than other datasets.

One important advantage of Preqin's database over others is that I can directly observe the names of the fund and GPs that invested in a portfolio firm. For instance, the Burgiss dataset is known to have more detailed cash flow information, but fund names are anonymized, and I cannot match the data to individual portfolio firms. In addition, I can observe data on funds that invest in European companies, due to Preqin's global coverage. Within the Preqin dataset, I match individual fund cash flow data to the list of buyout transactions. Preqin's buyout transaction data records each fund that invested in a certain target company and allows me to create a panel with matched portfolio firms for each fund quarter. Next, to determine each fund's fundraising periods and fundraising success, I match the fund's subsequent fundraising information for each fund.

3.2 Data on portfolio firm financial statement information

The second dataset I use is from Amadeus, a Bureau van Dijk database. Amadeus collects detailed financial statement information on both public and private companies from Europe, mainly from prominent national financial statement information compilers (Burgstahler, Hail, and Leuz, 2006). Since Amadeus only keeps 10 years' worth of recent financial statements, I combine historical information downloaded in 2012 and 2020, an approach similar to Breuer (2021). By doing so, I can maximize match quality with the Preqin dataset (since

I have more firm-years available) and reduce the survivorship bias of the Amadeus data.[13] The combined dataset has more than 162 million observations. For consistent currencies with Preqin, I convert all financial variables into US dollars, using the exchange rates stored in Amadeus.

3.3 Matching two datasets and sample creation

I hand match Amadeus to the Preqin master data, using company name. For each portfolio firm identified in the Preqin master dataset, I match financial statements one calendar year before the reported quarter. I use one-year lagged financials because many portfolio firms receive annual audits of their financial statements that take multiple months to complete. Breuer (2021) shows that private firms take a maximum of 13 months to disclose their financial statements in many European countries. This decision is also consistent with the anecdotal observation that many fund reports use one-year lagged financial statement information to value their portfolio firms. Also note that the fund-level valuation data is quarterly, whereas the financial statements are annual. According to conversations with the practitioners and my examinations of sample valuation reports, valuations are calculated with the latest annual report (rather than using updated financials every quarter).

The above process yields a panel of fund-level quarterly NAVs matched with portfolio firm financial information. I then take the following additional steps to refine my sample. I delete any portfolio firm-year observations that were before the transaction date or after PE exit, to ensure these firms were owned by the GPs at the reporting date. Following prior studies, I also delete funds with vintages after 2018, due to the lack of valuation information from these funds. Finally, I collapse the data to the fund-quarter level, since the fund NAVs are aggregated each quarter. To do so, I sum all the portfolio firm earnings (i.e., EBITDA, sales, and total assets) and deflate them by fund size. Both portfolio firm earnings and fund

[13] Amadeus (and the Bureau van Dijk datasets) drops firms if they are deemed inactive for a number of years. An old Amadeus dataset would provide firms that would otherwise have been deleted from the new dataset.

size are denoted in US dollars and should mitigate concerns arising from different currencies used in portfolio firms. The sample consists of 8,709 observations.

3.4 Descriptive statistics

Table 1 shows descriptive statistics of the funds and portfolio firms, of which there are 410 funds and 1,838 portfolio companies. Panel A presents GP (first two columns) and portfolio firm (last two columns) headquarters countries; about 45.1% of the GPs are from the United States, and 29.5% are from the United Kingdom. Other notable countries include France, the Netherlands, and Sweden. As discussed in Section 3, the high representation of US funds is likely because Preqin mainly collects data through FOIA requests to US pension funds.

The last two columns show the number of portfolio firms' headquarters countries. UK firms show the highest representation in my sample (637 firms), with France, Sweden, and Germany following. This is consistent with the statistics reported in Invest Europe (2019) that the United Kingdom and France are the largest PE markets in Europe.

Panel B reports descriptive statistics of fund characteristics. I summarize fund descriptive statistics based on fund reputation and for the entire sample. By construction, funds with low reputation GPs are much smaller in average size ($897.4 million) and fund number (2.56), compared to high reputation GPs ($3.6 billion in size and 6.4 fund number). Fund vintage is similar for both types of funds, ranging from 2005 to 2014 (p25 and p75). The reported fund size and number are qualitatively similar to the statistics reported by Hüther (Forthcoming).

Table 2 presents the descriptive statistics of the full sample (Panel A) as well as subsamples partitioned by reputation (Panel B). Variable FundraiseFlag has a mean value of 0.112 for all samples, with little difference between low (0.101) and high (0.116) reputation GPs. NAV/Sales multiple has a value of 9.488, and high reputation GPs have a higher mean value (10.550) than that of low reputation GPs (6.557); this is also true for NAV/EBITDA multiple (low reputation sample mean 26.182, high reputation mean 38.986), although the difference is smaller than that of NAV/Sales. The means are comparatively higher than Liu, Nissim, and Thomas (2002), who study valuation multiples in a public firm setting. The high mean seems to be driven by observations in the right tail of the distribution, especially given that the median values are substantially lower than the mean (NAV/Sales and NAV/EBITDA median 2.213 and 12.441, respectively). I winsorize the multiples at the 5% level to alleviate the concern (more details in Section 4.1). The mean number of portfolio firms (ln(# of Portfolio Firms)) in a given quarter is higher for funds with high reputation GPs (mean 1.720) than for funds with low reputation GPs (mean 1.465). Funds managed by low reputation GPs are slightly older than those managed by high reputation GPs in terms of fund age (logged value mean 1.860 versus 1.699) and younger in terms of GP age (logged value mean 2.703 versus 3.157).

Table 3 reports the descriptive statistics of the portfolio firm-level sample, for the full sample (Panel A) and for samples partitioned by reputation (Panel B). Portfolio firms owned by low (high) reputation GPs have 0.001, 0.004, -0.035, and -0.080 (-0.010, -0.145, and 0.108) mean abnormal accruals, abnormal production costs, and abnormal discretionary expenses, respectively.[14] The portfolio firms of low reputation GPs have higher (lower) production costs (discretionary expenses) than those of high reputation GPs; this is consistent with the idea that low reputation GP portfolio firms show more EM (three of four measures statistically significant at least at the 5% level, as shown in Panel B), consistent with the results from Wongsunwai (2013), who find EM is stronger for investments backed by lower quality VC funds.

Consistent with expectations, low reputation GP portfolio firms have stronger EM than high reputation ones, across all three variables. Low reputation GP portfolio firms are larger in size, have lower leverage, are less profitable, and have lower growth.

[14]Prior studies mostly have mean values of zero across all EM variables. The deviation from zero suggests that PE-backed firms have significantly different levels of EM, consistent with Katz (2009). In untabulated results, the mean values of EM variables of the entire sample are all zero.

4 Research design

4.1 Testing abnormal increases in fund valuation multiples

To test my first prediction, I partition my sample by GP reputation and estimate Equation 1. I choose to divide my sample by reputation because prior studies have emphasized the importance of reputation in fundraising and how it can lead to myopic decisions during fundraising periods. For example, Barber and Yasuda (2017) show that low reputation GPs time the fundraising period to coincide with their existing fund's peak performance. Brown et al. (2019) also show that fund manipulation occurs for low-performing funds because the payoffs from doing so outweigh the costs from LPs seeing through the embellished performance.

I base my measure of reputation on the proxy developed in Barber and Yasuda (2017). Conceptually, reputation is measured using GP's fund size, age, and performance. They define low reputation GPs as satisfying the following three conditions, measured at fund inception:[15] funds (i) that do not have top quartile performing funds more than five years old as of fund inception, (ii) that have raised less than three funds, and (iii) that have raised less than $1 billion in cumulative capital. I adjust this definition of low reputation to funds that satisfy ((i) and (ii)) *or* ((i) and (iii)). The reason for deviating from the approach of Barber and Yasuda is because low reputation GPs (with their definition) are under-represented in my setting, which reduces the power of my tests. Specifically, only 27 (out of 410) funds are classified as low reputation using Barber and Yasuda's definition, which is only about 6.5% of the funds I have in my sample (contrary to the 40% reported in their paper). The large difference in composition of high/low reputation GPs in my sample, compared to Barber and Yasuda's, is because I use the European setting and I have a longer period sample. US funds (which comprise 45% of the funds in my sample; see Section 3.4

[15] Because each fund's GP reputation is measured at inception, I do not change reputations even if a GP of a particular fund achieved high reputation status in the middle of the fund's life. In this case, the change will only happen after subsequent fundraising.

for a detailed description) that invest in European firms tend to have high reputation. My sample consists of fund-quarters from 2000 to 2019, and naturally, there will be more funds that have had first quartile funds more than five years old than Barber and Yasuda's sample (from 2003 to 2012).[16]

Using the partitioned sample, I estimate the following model:

$$\ln\left(\frac{NAV_{i,t}}{\sum_{j=1}^{n} Performance_{i,j,t-1}}\right) = \beta_1 FundraiseFlag_{i,t} + \gamma' X_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t} \quad (1)$$

where $\ln\left(\frac{NAV_{i,t}}{\sum_{j=1}^{n} Performance_{i,j,t-1}}\right)$ is the fund-level natural log of net asset value, divided by sum of portfolio firm EBITDA or sales. $FundraiseFlag_{i,t}$ is a dummy variable that equals one if a GP j managing fund i is raising its subsequent fund at quarter t and zero otherwise. A fund is considered to be raising funds zero to four quarters before the subsequent fund's closing calendar quarter, which is directly observable from Preqin data.[17] I take this approach, instead of using a post-fundraising indicator as my variable of interest (as do Barber and Yasuda (2017)), to precisely locate activities during fundraising quarters, rather than testing for decreases after fundraising quarters. (I graphically show the reversals in multiples and EM in Figures 3 and 4.) This method also alleviates the concern from Brown et al. (2019) that lower post-fundraising NAVs may be stemming from GPs' reduced attention to interim funds because deciding how high the multiples should be is a relatively simple process (compared to monitoring individual portfolio firms) and does not require additional attention from the GPs .[18] For funds that do not have subsequent funds, I define

[16]In Table IA1 of the internet appendix, I re-estimate my analysis using an alternative definition, where a low reputation GPs are defined as funds that satisfy all three following conditions: funds (i) that do not have top quartile performing funds more than five years old as of fund inception, (ii) that have raised less than *the median number of funds in my sample*, and (iii) that have raised less than \$1 billion in cumulative capital. The results are qualitatively similar.

[17]Studies have also used subsequent fund's first observed cash flow date as the fundraising closing date. While this also is a reasonable assumption, an advantage of my approach is that the close date is directly observable. In Table IA2, I use the alternative date (i.e., the subsequent fund's first observed cash flow date) as the fundraising closing date and find qualitatively similar results.

[18]Brown et al. (2019) argue that the reversal in NAVs post fundraising can occur because of GPs' reduced attention to their existing fund investments.

a fundraising quarter to be 13 to 28 quarters since inception, following Barber and Yasuda (2017).[19] $\sum_{j=1}^{n} Performance_{i,j,t-1}$ is either the sum of EBITDA or the sum of sales. I use EBITDA instead of net income since EBITDA is known to estimate firm values well in LBOs (e.g., Kaplan and Ruback, 1995). This is because EBITDA calculates the earnings before interest expenses, which consume most of the earnings of the portfolio firm (since LBOs by definition involve high debt levels put on the portfolio firms). Consistent with this argument, EBITDA is the most commonly used metric in the PE industry (IPEV, 2018). $\gamma' X_{i,t}$ denotes a battery of fund-level control variables I employ in the model and largely follows the literature on PE fund reporting (e.g., Barber and Yasuda, 2017). The controls include the natural log of the number of active portfolio firms in a given fund quarter, the natural log of fund age, and the natural log of GP age. I include the natural log of the number of portfolio firms to capture new investments/exits in a given fund. The natural log of fund age controls for the fund's life-cycle; multiples may be systematically different for funds that just began investing from funds that are preparing to exit most of their investments. Finally, the natural log of GP age controls for the GP's experience and reputation. More experienced, well-known GPs may have access to better investments and therefore could be able to justify higher valuation multiples.[20] See Table A1 in the appendix for a complete list of variable definitions. I also include fund (α_i) and calendar year-quarter (α_t) fixed effects for time-invariant fund and time attributes, respectively. Standard errors are clustered at the fund level.

One caveat in this approach is that the measure $\sum_{j=1}^{n} Performance_{i,j,t-1}$ is a simple sum of all portfolio firms and does not take the actual percentage ownership of the buyout fund, due to data constraints. (Preqin does not report a specific percentage stake of buyout transactions.) However, since buyouts typically involve more than 50% stake acquisition in

[19] To avoid possible measurement errors of the fundraising quarter, in Table IA5 I randomly select fundraise dates that matches the same distribution with my sample, and re-estimate the regressions 100 times. I do not find any meaningful results for both fund and portfolio firm tests.

[20] Barber and Yasuda (2017) use fund size and buyout market fund return as controls; these are controlled for using fund and year-quarter fixed effects, respectively. Brown et al. (2019) use fund cash inflow/outflow as controls; controlling for the number of portfolio firms produces a similar effect.

a target firm, I expect the measurement error to be not too severe. Nevertheless, to cope with this issue, the variable $\ln\left(\frac{NAV_{i,t}}{\sum_{j=1}^{n} Performance_{i,j,t-1}}\right)$ is winsorized at the 5% level; this is also consistent with Barber and Yasuda (2017), who winsorize the NAV variable at the 5% level. (Winsorizing at the 1% level yields qualitatively similar results; the results are shown in Table IA3.) All other continuous variables are winsorized at 1% level.

Note that I consider positive value multiples by computing natural logs of the valuation multiples. Although this process would not affect the sales multiple (since sales are greater than zero), it discards negative EBITDA multiples. I find this assumption reasonable because negative multiples are treated differently than positive ones (Barth, Beaver, and Landsman, 1998; Ferreira et al., 2019; Hayn, 1995).[21]

4.2 Testing abnormal increases in portfolio firm earnings management

In this section, I discuss the research design to test my second hypothesis, whether firms held by low reputation GPs use EM to inflate their financial performance. To be more specific, EM can be largely classified into two forms: accruals earnings management and real earnings management. The former mainly requires taking aggressive accounting policies, such as recognizing revenues early and expenses late. On the contrary, REM uses real actions to achieve higher earnings in the short-term. For example, firms can build abnormal levels of inventory to reduce cost of goods sold per unit (abnormal production costs),[22] or excessively reduce expenses that may help a firm in the long-run, such as R&D expenses and marketing costs (abnormal discretionary expenses). I test for both accruals and real EM because GPs can influence their portfolio firms to engage in both methods, by obtaining strong control over their investments through majority stake ownership, board memberships,

[21] According to interviews with practitioners, when a fund has negative EBITDA multiples, GPs provide multiples using alternative multiples (e.g., NAV/Sales) or use different valuation methods (e.g., value the investment at cost).

[22] Producing more units spreads fixed overhead costs and reduces fixed costs per unit. Therefore, the total cost per unit declines (Roychowdhury, 2006).

and hiring management teams with aligned interests.

Because controlling for firm performance is critical for my research design, I use performance-matched EM measures developed by Kothari, Leone, and Wasley (2005).[23] Specifically, I use three EM proxies. To measure AEM, I use performance-matched Modified Jones accruals (with augmented ROA) modeled by Kothari et al. (2005); to capture REM, I use the REM proxies (again performance-matched) developed by Roychowdhury (2006), (ii) abnormal production costs, and (iii) abnormal discretionary expenses,[24] which measure overproduction and excessive cost cuts, respectively. I predict positive, positive, and negative signs for each measure, respectively. The exact estimation methods and the intuition for the proxies are described in detail in Appendix C.

Subsequently, I use firm-level data (the sample before I collapse into fund-quarters) and estimate the following regression:

$$EM_{i,j,t-1} = \beta_1 FundraiseFlag_{i,t} + \gamma' X_{i,j,t-1} + \alpha_i + \alpha_t + \alpha_j + \alpha_{c,ind,t-1} + \epsilon_{i,j,t-1} \qquad (2)$$

where $EM_{i,j,t-1}$ is one of the earnings proxies for portfolio firm j (invested by fund i) measured at year $t-1$;[25] $FundraiseFlag_{i,t}$ equals one if a portfolio firm reporting date is classified as a fundraising period of the fund and zero otherwise; $\gamma' X_{i,j,t-1}$ is a vector of portfolio firm-level control variables discussed by Dechow, Ge, and Schrand (2010), and includes firm size (inverse of total assets), leverage, profitability (ROA), and sales growth. α_i, and α_t, denote fund fixed effects and calendar year-quarter fixed effects, respectively, and α_j and $\alpha_{c,ind,t-1}$ denote portfolio firm fixed effects and portfolio firm country-industry-year fixed effects (SIC Code one-digit), respectively. Standard errors are clustered at the fund and portfolio firm country-industry-year (two-way) level.

[23] Table IA4 uses non-performance-matched EM variables and yield qualitatively similar results.

[24] Note that I use the entire operating expenses to proxy for discretionary expenses because many European private firms aggregate R&D and marketing expenses into operating expenses.

[25] Recall that year $t-1$ is one calendar year before the year of time t, the reporting date at the fund level. The reason behind is decision is delineated in section 4.1.

4.3 Using EM variables as the dependent variable

One aspect that is important to discuss is that the EM variables are obtained through a two-step process. EM variables, as described in Appendix C, obtain residuals from regressing *normal* accruals, production costs, or discretionary expenses on a variety of control variables for each country-industry-year. A caveat with using variables using this procedure as the dependent variable is that the analysis could yield biased coefficients if not used properly. Specifically, Chen et al. (2018) have shown that using these variables as dependent variables could result in both type I and type II errors.

To address this concern, Chen et al. (2018) suggest three solutions. The first and most widely used solution is to use *normal* EM rather than the residuals (i.e., abnormal EM) as dependent variables and estimate a single-step regression. The second solution is to regress abnormal EM variables on residuals from regressions of the second-step regressors on first-step regressors. However, these two solutions cannot be used in my setting, because the first-step residuals are obtained using the entire Amadeus database (i.e., all European private firms available in the database) but the variables used in my second-step regression is only available to firms owned by buyout funds, which is extremely small (0.024%) compared to the entire Amadeus database. In other words, the variable FundraiseFlag is only available for buyout fund portfolio firms, because non-portfolio firms are not fundraising in a PE setting. Therefore, I follow the third solution from Chen et al. (2018): I combine variables used in the first-step as controls in addition to the independent variables used in the second step. For instance, to test whether abnormal accruals of the portfolio firms increase during fundraising periods (i.e., Equation 2), I include lagged inverse total assets, property plant and equipment, changes in sales, and ROA (all scaled by lagged total assets), in addition to the control variables delineated in Equation 2. Chen et al. confirm that this approach generates unbiased coefficients and reliable t-statistics.

4.4 Entropy balancing

The research design discussed so far cannot rule out the alternative explanation that the results may occur from GPs timing their fundraising periods. This explanation is important because Barber and Yasuda (2017) show that low reputation GPs also time their fundraising periods when the performance is at its peak. To address this concern, I conduct entropy balancing so that the treated quarters (fundraising quarters) have similar fundraising timing attributes to the control quarters (nonfundraising quarters). Entropy balancing controls for fundraising timing between fundraising and nonfundraising quarters and helps me distinguish whether the result is from manipulation or from timing. This method provides an important advantage over propensity-score matching by generating a higher degree of covariate balance than propensity-score matching (Hainmueller, 2012).

To match the characteristics between treated and control quarters, for each reputation sample, I require the control quarters to have similar fund age, NAV, fund size, distribution, and fundraising year. Specifically, I match the first (mean) and second (variance) moments of the treated quarters and control quarters using these attributes. Therefore, the control quarters are quarters that have similar fund age, valuation, fund size, distribution, and time. As shown in Table IA6 and Table IA7, after entropy balancing, fund-related characteristics are well matched. With the entropy-balanced sample, I re-estimate equations 1 and 2.

5 Results

5.1 Valuation multiples regression results

Figure 3 depicts the mean valuation multiples before and after fundraising. In Panel A (Panel B), the X-axis shows quarters, relative to the fundraising close quarter, and the Y-axis represents levels of the natural log of NAV divided by the sum of EBITDA (sales) for each quarter. The blue line (red line) shows mean values for low (high) reputation GPs.

Consistent with my hypothesis and prior research, funds with low reputation GPs exhibit an increase in valuation multiples immediately before fundraising close and sharp reversals post fundraising. EBITDA multiples of low reputation GP funds in Panel A show a sharp peak at the fundraising close quarter (quarter 0), and the multiples begin to quickly erode. sales multiples for low reputation GP funds (Panel B) maintain the elevated multiples up to three quarters post fundraising. On the contrary, both multiples are lower before fundraising close for funds with high reputation GPs, indicating some degrees of conservative reporting.

Table 4 presents the main test results of the first hypothesis. Panel A (Panel B) reports coefficients using the low reputation GP sample (high reputation GP sample). For both panels, columns (1) and (2) report results for the main sample, and columns (3) and (4) report results for the entropy-balanced sample. The research design used in the entropy-balanced samples should rule out the timing hypothesis by matching fundraising quarters to nonfundraising quarters with similar fundraising motives. (See Section 4.4 for details.) Columns (1) and (3) ((2) and (4)) use EBITDA (sales) multiples as the dependent variable. Coefficients from all columns in Panel A indicate a statistically significant increase in both EBITDA and sales multiples of low reputation GP funds during fundraising. Economically, EBITDA (sales) multiples increase by 18.2% (22.7%), compared to nonfundraising periods, which translates to an increase of approximately 4.77x (1.49x). Similar to the coefficients from columns (1) and (2), the coefficients are significant for tests using the entropy-balanced sample. The coefficients are slightly lower, showing 0.157 and 0.170 in columns (1) and (2), respectively.

On the contrary, in Panel B, I find negative coefficients (statistically significant for EBITDA multiples) for high reputation GP funds; fundraising is associated with an 11.9% decrease in EBITDA multiples, which translates to a drop of 4.64x; the results using entropy-balanced sample (columns (3) and (4)) also demonstrate a significant drop in valuation multiples. The results are consistent with Brown et al. (2019) who find a more conservative valuation during fundraising periods for high reputation GPs.

In the bottom row of Panel A, I compare coefficients FundraiseFlag for each column in different Panels (e.g., column (1) of Panel A versus column (1) of Panel B) by conducting SUR test, which examine the difference of coefficients between low reputation and high reputation samples. SUR tests using the both main and entropy-balanced samples display statistically significant χ^2 values (6.36 and 5.69, 18.19 and 23.57 respectively; significant at the 5% and 1% level, respectively). Overall, the results reported in this table support the argument that the increased multiples are from manipulation rather than timing fundraising periods.

5.2 EM regression results

Figure 4 shows the levels of EM pre and post-fundraising. Panels A, B, and C report mean values of abnormal accruals, abnormal production cost, and abnormal discretionary expenses, respectively. For all panels, the blue line (red line) represents portfolio firms owned by low reputation (high reputation) GPs. Consistent with my hypothesis, I observe abnormal levels[26] and reversals of EM of portfolio firms before and after fundraising.

Table 5 presents the results of the regressions testing the second hypothesis. Panel A show the coefficients for firms owned by low reputation GPs, using abnormal accruals, abnormal production costs, and abnormal discretionary expenses as the dependent variables; the last three columns reports the results using the entropy-balanced sample. Consistent with the reputation results shown in Table 4, portfolio firms owned by low reputation GPs show strong signs of EM across two of the three regressions. In economic terms, portfolio firms during which their owner GPs are fundraising show 3.8%, and 14.3% increase, and a 7.1% decrease in abnormal accruals, abnormal production costs, and abnormal discretionary expenses respectively, consistent with my predictions. Considering the normal accruals of my sample are -0.018 and the changes in accounts receivables is 0.028, the effect is economically significant. On the other hand, I do not find a statistically significant result using abnormal

[26] I observe lower abnormal discretionary expenses during fundraising, considered to be indicative of EM.

discretionary expenses, although the sign of the coefficient is consistent with the prediction.

In contrast, in Panel B, I do not find any statistically meaningful results for firms owned by high reputation GPs. Similar to Panel A, columns (1), (2), and (3) test using abnormal accruals, abnormal production cost, and abnormal discretionary expenses as dependent variables for the main sample, respectively, while columns (4), (5), and (6) use the entropy-balanced sample.

SUR tests reported at the bottom row of Panel A indicate that the low reputation/high reputation samples have significantly different coefficients at the 10% level. In particular, when comparing coefficients using the entropy-balanced sample, low reputation and high reputation GPs have significantly different coefficients for all regressions. Specifically, the χ^2 SUR test values for column (4), (5), and (6) are 5.49 (significant at the 5% level), 21.00 (significant at the 1% level), and 7.15 (significant at the 1% level), respectively. This result supports the findings of Brown et al. (2019), who find more conservative reported returns for high reputation GPs. Taken together, the results suggest that low reputation GPs use EM to inflate portfolio firm earnings.

5.3 Falsification test using portfolio firms with multiple investors

To further support my main results, I exploit the amount of influence an investor can make on their portfolio firms. More specifically, I explore whether portfolio firms invested by multiple investors show similar behavior when one of the investors is raising subsequent funds. I anticipate that one investor would have a much lesser influence on their portfolio firms if multiple investors are invested in a portfolio firm. Therefore, even if one GP has the incentive to influence its portfolio firm to engage in EM (due to fundraising), other GPs that are not fundraising would prevent the motivated GP to do so, because of potential long-term harmful outcomes that may arise from conducting EM.

To test this idea, I pool low reputation *venture capital* and buyout investments that have *more than two PE funds* as shareholders (i.e., 'club deals') and test whether these firms manage earnings when one of the GPs is raising funds, by re-estimating Equation 2.[27] I present the results in Table 6; I do not find any statistically meaningful results for these portfolio firms, which is consistent with the argument that one investor would face a more difficult time influencing its portfolio firm if other shareholders are involved.

5.4 Effects of PE ownership

An alternative interpretation of my results discussed in Section 5.2 could be that the results are simply from the effects of buyout fund ownership, specifically that the funds enhance the financial performance of the firms they invest in. Several studies have shown that buyout fund ownership relates to better operational efficiency (e.g., Cohn et al., 2014; Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda, 2014; Guo et al., 2011; Kaplan, 1989). If this is the case, I would expect to observe similar effects when I compare the effects of PE ownership. Therefore I test whether EM proxies significantly change PE ownership. Specifically, I estimate the following regression:

$$EM_{i,j,t-1} = \beta_1 PEOwn_{i,j,t-1} + \gamma' X_{i,j,t-1} + \alpha_i + \alpha_t + \alpha_j + \alpha_{c,ind,t-1} + \epsilon_{i,j,t-1} \tag{3}$$

where the variable of interest $PEOwn_{i,j,t-1}$ is a dummy variable that equals one if the portfolio firm is under PE ownership and zero otherwise. I remove portfolio firm-years under fundraising years (under PE ownership) to clearly show the effects of PE ownership without fundraising motives.

Table 7 reports the regression coefficients. Columns (1)-(3) show results for low reputation GP portfolio firms, and columns (4)-(6) for high reputation GP portfolio firms. In columns (1)-(3) (portfolio firms owned by low reputation GPs), I do not find any statistically significant results, mitigating the concern that the results may be simply driven by PE ownership. Furthermore, results in columns (4)-(6) (high reputation GP portfolio firms)

[27] For brevity, I present results using the main sample. Results using entropy-balanced sample, reported in Table IA8 Panel A, are similar.

demonstrate a *decrease* in abnormal accruals and an *increase* in abnormal discretionary expenses (which suggests lower EM), which do not support the alternative interpretation.

5.5 Reversals post fundraising

Another possible concern is that the abnormal surge in multiples and EM may be an efficient outcome, given that studies have shown that the fund valuations are often conservative during nonfundraising times (e.g., Brown et al., 2019; Ferreira et al., 2019; Jenkinson et al., 2013). In other words, GPs may have reported more conservative multiples/earnings when they are not fundraising, and may be reporting them at normal levels when fundraising. To address this argument, I graphically present valuation multiples pre and post-fundraising in Figure 3 (also discussed in Section 5.1). Specifically, Panel A (Panel B) presents the mean natural log of EBITDA (sales) multiples. If the increase was an efficient outcome, one would expect the increase would remain persistent even after fundraising. However, I observe a sharp decline in both EBITDA and sales multiples for funds managed by low reputation GPs one to four quarters after fundraising. The effect is sharper for EBITDA multiples, which is known to be the most commonly used metric in the PE industry (Grant Thornton, 2015).

In a similar vein, Figure 4 presents mean values of EM variables pre and post-fundraising. Panel A, B, and C show mean values for abnormal accruals, abnormal production cost, and abnormal discretionary expenses, respectively. Across all variables, I observe results consistent with my prediction. Portfolio firms owned by low reputation GPs exhibit higher AEM and REM approximately four quarters before fundraising close. Post fundraising close, I observe a sharp decline in EM, a result consistent with the findings in Figure 3.

In sum, the evidence suggests a sharp reversal post fundraising for both multiples and EM, because it implies that the GPs are unable to sustain the high multiples and managed earnings. If the higher multiples and EM were efficient, low reputation GPs should have maintained them at higher levels even after fundraising, as high reputation GPs do (as seen in the figures). This stands counter to the argument that the increase during fundraising is an efficient outcome.

5.6 Coincidence with portfolio firm exit timing

The third alternative explanation is that fundraising timing may coincide with the portfolio firm's exit timing. As Gompers (1996) suggests, GPs may prematurely exit their portfolio firms to succeed in fundraising, and the results may be driven by portfolio firms with impending exits. In this case, EM may occur, but the primary aim would be to maximize the exit values, as in the results of Teoh, Wong, and Rao (1998), who show a stronger degree of EM before IPOs. To alleviate the concern, in Table 8, I drop portfolio firm-years with less than two years before their exit dates and re-estimate Equation 2 for low reputation GP portfolio firms.[28] The results remain qualitatively similar to the results shown in Table 5.

5.7 Consequences

A remaining important question is whether different embellishing strategies incur different outcomes. While prior studies (e.g., Barber and Yasuda, 2017; Brown et al., 2019) have shown that NAV management is looked through by the LPs, it is possible that GPs that use certain strategies may be able to raise subsequent funds. For instance, one conjecture could be that managing NAVs through portfolio firm earnings could have a much lower chance of detection than through increasing fund valuation multiple, because valuation multiples are much easier to calculate (e.g., by comparing to comparable firms or funds) than backing out managed earnings of each portfolio firm.

To test whether different performance management strategies yield different fundraising outcomes, I take the following steps. First, for each sample, I take the mean of valuation multiples (or EM) of a fundraising/nonfundraising period for each fund. There is one

[28] Table IA8 Panel B displays the results using the entropy-balanced sample. The results are qualitatively similar.

observation per fund. Next, I estimate the following regression:

$$
\begin{aligned}
FinalFund_i = {} & \beta_1 Multiple_i(MeanEM_i) \times FundraiseFlag_i + \beta_2 Multiple_i(EM_i) \\
& + \beta_3 FundraiseFlag_i + \gamma' X_i + \alpha_c + \alpha_v + \alpha_y + \epsilon_i
\end{aligned}
\tag{4}
$$

where $FinalFund_i$ equals one if there is no subsequent fund reported in the Preqin database, and zero otherwise; $Multiple_i$ and EM_i are the *mean* of valuation multiples (i.e., ln(NAV/EBITDA) or ln(NAV/Sales)) and the *mean* of EM proxies, respectively; $FundraiseFlag_i$ equals one if the observation is fundraising period, and zero otherwise; $Controls_i$ include fund-related characteristics, and include the natural log of fund size, mean of the natural log of the number of portfolio firms, mean of the natural log of fund age, mean of the natural log of GP age; α_c, α_v, α_y denote GP country, vintage, and fundraise year fixed effects, respectively.

Table 9 presents the results. Panel A (Panel B) shows results using valuation multiples (EM). In Panel A, columns (1) and (2) ((3) and (4)) report regression results for the low reputation GP (high reputation GP) sample. My coefficient of interest, MeanMultiple $\times$ FundraiseFlag is positively related to the dependent variable, while the main effect MeanMultiple is negative, with similar economic magnitudes. This suggests that while higher multiples valued during nonfundraising periods are interpreted as a positive sign to potential investors, having higher multiples during *fundraising* periods does not necessarily help fundraising outcomes. This is consistent with prior literature that shows the investors look through manipulated current fund performance (Brown et al., 2019).

In Panel B, columns (1), (2), and (3) use the low reputation GP sample, and columns (4), (5), and (6) use the high reputation GP sample. In column (1), coefficient MeanAccruals $\times$ FundraiseFlag is negatively significant, implying that GPs which use more abnormal accruals are able to raise subsequent funds to some extent.

Collectively, the findings suggest that the probability of subsequent fundraising for low reputation GPs differs for each manipulation method. Specifically, GPs that manipulate at the portfolio firm-level face a higher probability of raising a next fund, while those who manage at the fund-level are likely to fail. This implication is somewhat in contrast to previous findings (e.g., Barber and Yasuda, 2017; Brown et al., 2019) who find fundraising attempts are always unsuccessful for low reputation GPs who attempt to manage interim fund valuations.

6 Conclusion

In this paper, I investigate whether and how PE funds inflate their valuations during fundraising. I find novel evidence that funds managed by low reputation buyout GPs increase their valuation multiples during fundraising periods as well as portfolio firm earnings through AEM and REM. The results are consistent with the manipulation hypothesis more than the fundraising timing hypothesis. My findings are robust to a battery of alternative explanations. I also propose that low reputation GPs conducting some form of EM are somewhat successful in raising subsequent funds.

My paper contributes to the academic literature in three ways. First, it contributes to the PE literature by showing the mechanisms behind NAV inflations of PE funds during fundraising periods. My findings suggest that low reputation GPs manipulate fund returns via valuation multiples at the fund level and EM at their portfolio companies. Second, I contribute to the literature that studies the valuation of illiquid assets, by demonstrating that fundraising and fund managers' incentives can influence the relationship and the accuracy of the valuations because the underlying investments lack quoted market prices. Finally, I contribute to literature on the transparency of private firms by (i) showing private firms under long-term institutional investors can manage earnings when the investors face myopic motives, (ii) emphasizing that valuation multiples could be manipulated in PE fund settings, and (iii) enhancing the understanding of corporate transparency in private firm settings.

References

Acharya, V. V., Gottschalg, O. F., Hahn, M., & Kehoe, C. (2013). Corporate governance and value creation: Evidence from private equity. *Review of Financial Studies*, *26*(2), 368–402.

Acharya, V. V., Kehoe, C., & Reyner, M. (2009). Private equity vs. PLC boards in the U.K.: A comparison of practices and effectiveness. *Journal of Applied Corporate Finance*, *21*(1), 45–56.

Agarwal, V., Vashishtha, R., & Venkatachalam, M. (2018). Mutual fund transparency and corporate myopia. *Review of Financial Studies*, *31*, 1966–2003.

Altamuro, J., & Zhang, H. (2013). The financial reporting of fair value based on managerial inputs versus market inputs: Evidence from mortgage servicing rights. *Review of Accounting Studies*, *18*(3), 833–858.

Barber, B. M., & Yasuda, A. (2017). Interim fund performance and fundraising in private equity. *Journal of Financial Economics*, *124*(1), 172–194.

Barth, M. E., Beaver, W. H., & Landsman, W. R. (1998). Relative valuation roles of equity book value and net income as a function of financial health. *Journal of Accounting and Economics*, *25*(1), 1–34.

Berfeld, N. (2022). The More You Know: How Auditors Mitigate Opportunism in Fair Value Measurements. *Boston College Working Paper*.

Bernard, D., Burgstahler, D., & Kaya, D. (2018). Size management by European private firms to minimize proprietary costs of disclosure. *Journal of Accounting and Economics*, *66*(1), 94–122.

Bernstein, S., & Sheen, A. (2016). The Operational Consequences of Private Equity Buyouts: Evidence from the Restaurant Industry. *Review of Financial Studies*, *29*(9), 2387–2418.

Breuer, M. (2021). How Does Financial-Reporting Regulation Affect Industry-Wide Resource Allocation? *Journal of Accounting Research*, *59*(1), 59–110.

Brown, G. W., Gredil, O., & Kaplan, S. N. (2019). Do Private Equity Funds Manipulate Reported Returns? *Journal of Financial Economics*, *132*(2), 267–297.

Brown, G. W., Harris, R. S., Jenkinson, T., Kaplan, S. N., & Robinson, D. T. (2015). What Do Different Commercial Data Sets Tell Us About Private Equity Performance? *University of North Carolina Working Paper*.

Brown, J., Carman, E., & Giaimo, C. (2018). Regulatory issues in marketing PE funds. *Ropes & Gray Yearbook*, *December*, 36–38.

Burgstahler, D. C., Hail, L., & Leuz, C. (2006). The importance of reporting incentives: Earnings management in European private and public firms. *The Accounting Review*, *81*(5), 983–1016.

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, *73*(3), 305–333.

Chakraborty, I., & Ewens, M. (2018). Managing performance signals through delay: Evidence from venture capital. *Management Science*, *64*(6), 2875–2900.

Chen, W., Hribar, P., & Melessa, S. (2018). Incorrect Inferences When Using Residuals as Dependent Variables. *Journal of Accounting Research*, *56*(3), 751–796.

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), 3259–3304.

Cohen, D. A., & Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, *50*(1), 2–19.

Cohn, J. B., Mills, L. F., & Towery, E. M. (2014). The evolution of capital structure and operating performance after leveraged buyouts: Evidence from U.S. corporate tax returns. *Journal of Financial Economics*, *111*(2), 469–494.

Da Rin, M., & Phalippou, L. (2017). The importance of size in private equity: Evidence from a survey of limited partners. *Journal of Financial Intermediation*, *31*, 64–76.

Davis, S. J., Haltiwanger, J., Handley, K., Jarmin, R., Lerner, J., & Miranda, J. (2014). Private equity, jobs, and productivity. *American Economic Review*, *104*(12), 4184–4204.

Dechow, P., Ge, W., & Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics*, *50*(2-3), 344–401.

Ferreira, P. H., Kräussl, R., Landsman, W. R., Borysoff, M. N., & Pope, P. F. (2019). Reliability and relevance of fair values: private equity investments and investee fundamentals. *Review of Accounting Studies*, *24*(4), 1427–1449.

Gompers, P. A. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics*, *42*(1), 133–156.

Gompers, P. A., Gornall, W., Kaplan, S. N., & Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, *135*(1), 169–190.

Gompers, P. A., Kaplan, S. N., & Mukharlyamov, V. (2016). What do private equity firms say they do? *Journal of Financial Economics*, *121*(3), 449–476.

Grant Thornton. (2015). *Private Equity valuations: Best practices and pitfalls: A Grant Thornton LLP 2015 survey.*

Gunny, K. A. (2010). The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research*, *27*(3), 855–888.

Guo, S., Hotchkiss, E. S., & Song, W. (2011). Do Buyouts (Still) Create Value? *Journal of Finance*, *66*(2), 479–517.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, *20*(1), 25–46.

Harris, R. S., Jenkinson, T., & Kaplan, S. N. (2014). Private equity performance: What do we know? *Journal of Finance*, *69*(5), 1851–1882.

Hayn, C. (1995). The information content of losses. *Journal of Accounting and Economics*, *20*(2), 125–153.

Hribar, P., & Collins, D. W. (2002). Errors in Estimating Accruals : Implications for Empirical Research. *Journal of Accounting Research*, *40*(1), 105–134.

Hüther, N. (Forthcoming). Do Private Equity Managers Raise Funds on (Sur)real Returns? Evidence from Deal-Level Data. *Journal of Financial and Quantitative Analysis*.

Invest Europe. (2019). *2018 European Private Equity Activity*.

Invest Europe. (2021). *Private Equity at Work. Employment & job creation across Europe*.

IPEV. (2018). *International Private Equity and Venture Capital Valuation Guidelines* (tech. rep.).

Jenkinson, T., Landsman, W. R., Rountree, B., & Soonawalla, K. (2020). Private Equity Net Asset Values and Future Cash Flows. *The Accounting Review*, (95).

Jenkinson, T., Sousa, M., & Stucke, R. (2013). How Fair are the Valuations of Private Equity Funds ? *University of Oxford Working Paper*.

Kaplan, S. N. (1989). The effects of management buyouts on operating performance and value. *Journal of Financial Economics*, *24*(2), 217–254.

Kaplan, S. N., & Ruback, R. S. (1995). The Valuation of Cash Flow Forecasts : An Empirical Analysis. *Journal of Finance*, *50*(4), 1059–1093.

Katz, S. P. (2009). Earnings Quality and Ownership Structure: The Role of Private Equity Sponsors. *The Accounting Review*, *84*(3), 623–658.

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, *39*(1), 163–197.

Kothari, S. P., Mizik, N., & Roychowdhury, S. (2016). Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. *The Accounting Review*, *91*(2), 559–586.

Lawrence, A., Siriviriyakul, S., & Sloan, R. G. (2016). Who's the fairest of them all? Evidence from closed-end funds. *The Accounting Review*, *91*(1), 207–227.

Lerner, J., & Schoar, A. (2004). The illiquidity puzzle: Theory and evidence from private equity. *Journal of Financial Economics*, *72*(1), 3–40.

Lerner, J., Schoar, A., & Wongsunwai, W. (2007). Smart institutions, foolish choices: The limited partner performance puzzle. *Journal of Finance*, *62*(2), 731–764.

Lisowsky, P., & Minnis, M. (2020). The Silent Majority: Private U.S. Firms and Financial Reporting Choices. *Journal of Accounting Research*, *58*(3), 547–588.

Liu, J., Nissim, D., & Thomas, J. (2002). Equity Valuation Using Multiples. *Journal of Accounting Research*, *40*(1), 135–172.

McKinsey. (2021). A year of disruption in the private markets. *McKinsey Global Private Markets Review*, (April).

Metrick, A., & Yasuda, A. (2010). The Economics of Private Equity Funds. *Review of Financial Studies*, *23*(6), 2303–2341.

Phalippou, L., & Gottschalg, O. (2009). The performance of private equity funds. *Review of Financial Studies*, *22*(4), 1747–1776.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, *42*(3), 335–370.

Roychowdhury, S., Shroff, N., & Verdi, R. S. (2019). The effects of financial reporting and disclosure on corporate investment: A review. *Journal of Accounting and Economics*, *68*(2-3), 101246.

Stein, J. C. (1989). Efficient Capital Markets, Inefficient Firms: a Model of Myopic Corporate Behavior. *Quarterly Journal of Economics*, *104*(4), 655–669.

Teoh, S. H., Wong, T., & Rao, G. R. (1998). Are accruals during Initial Public Offerings opportunistic? *Review of Accounting Studies*, *208*, 175–208.

Wongsunwai, W. (2013). The effect of external monitoring on accrual-based and real earnings management: Evidence from venture-backed initial public offerings. *Contemporary Accounting Research*, *30*(1), 296–324.

Zang, A. Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, *87*(2), 675–703.

Appendix A Variable definitions

Table A1: **Variable definitions**

Variable name	**Definition**
Variables used in tests	
Abn. Accruals	Abnormal accruals which measures accruals earnings management. See section Appendix C for detailed derivations.
Abn. Disc Exp	Abnormal discretionary expenses (operating expenses in my setting), and measures excessive cost cuts that temporarily increase earnings but could hurt long-term firm performance. See section Appendix C for detailed derivations.
Abn. Prod Cost	Abnormal production costs, and measures abnormal production. It is typically done by over-producing inventory than the demand forecast, and/or channel-stuffing. See section Appendix C for detailed derivations.
Chg Sales	Changes in sales (Current year sales - lagged year sales), scaled by lagged total assets.
FinalFund	Equals one if the GP was not able to raise a subsequent fund after the current fund, and zero otherwise.
FundraiseFlag	Equals one if a current fund's reported date is on or one-four quarters before fundraise close date of the subsequent fund, and zero otherwise.
FundraiseFlag_CF	Equals one if a current fund's reported date is on or one-four quarters before the first cash flow of the subsequent fund, and zero otherwise.
FundraiseFlag_Rand	Randomly generated dummy variable that matches the distribution of FundraiseFlag variable.
Fund size	Fund size, denoted in millions US$.
Fund #	Number of funds a GP has raised including the reported fund.
Inverse TA	Inverse of portfolio firm lagged total assets.
Leverage	Leverage of portfolio firm-year, total liabillities/total assets.
ln(NAV/EBITDA)	Natural log of fund NAV divided by sum of portfolio firm EBITDA reported in a given quarter.
ln(NAV/Sales)	Natural log of fund NAV divided by sum of portfolio firm sales reported in a given quarter.
ln(Fund Age)	Natural log of fund age.
ln(GP Age)	Natural log of GP Age. Measures GP experience.
ln(# of Portfolio Firms)	Natural log of the number of portfolio firms in a given fund-quarter.
MeanEM	Mean of one of three main earnings management proxies (abnormal accruals, abnormal production costs, abnormal discretionary expenses) for each fund during fundraising periods.

Table A1 – continued from previous page

Variable name	Definition
MeanMultiple	Mean of one of two valuation multiple proxies (i.e., ln(NAV/EBITDA), ln(NAV/Sales)) for each fund during fundraising periods.
ROA	Portfolio firm net income/total assets.
NAV	Valuation of the aggregate portfolio firm value, scaled by fund size.
PEOwn	Equals one if a portfolio firm is owned by a PE fund in a given year, and zero otherwise.
Vintage	The inception year of a fund.
Vocabulary related to private equity	
Limited Partners (LP)	Investors of private equity funds. Typically consist of endowment funds, pension funds, banks, and high net worth individuals. See Lerner, Schoar, and Wongsunwai (2007) for a description of various types of LPs.
General Partners (GP)	Private equity firms that manage the PE funds, such as KKR and Carlyle. GPs receive 2% of assets under management as management fees, and 20% of realized investment returns.
Buyout	A sub-type of private equity fund that engage in leveraged buyouts (LBOs). LBOs take majority equity stake in a target firm, and put increased amount of leverage onto their target firms.
Venture Capital (VC)	A sub-type of private equity fund that mainly invests minority equity stake in private firms.
Net Asset Value (NAV)	Typical valuation metric used to report valuations of underlying investments. In this paper, NAV is assumed to be a product of portfolio firm performance and applied valuation multiple.

Appendix B Sample PE fund report

Figure B1: **Sample PE fund report - Valuation rules**

This figure presents a sample PE fund report, created for the LPs. The figure illustrates the valuation methods used to value the fund's portfolio companies, in particular, the earnings multiple method. The red box in upper left corner confirms their compliance to IPEV guidelines; the box in bottom right corner explains their valuation methodology using market multiple method.

The key judgements in the fair valuation process are: -

(i) the Managers' determination of the appropriate application of the International Private Equity and Venture Capital guidelines ("IPEV") to each unlisted investment; and

(ii) the Directors' consideration of whether each fair value is appropriate following detailed review and challenge.

The judgement applied in the selection of the methodology used (see 4(c) below) for determining the fair value of each unlisted investment can have a significant impact upon the valuation.

Assumptions
The determination of fair value by the Manager involves key assumptions dependent upon the valuation methodology used. As explained below, the primary methodologies applied are i) Earnings Multiple, ii) Net Assets and iii) Price of Recent Investment. The multiples approach involves more subjective inputs than the other approaches and therefore presents a greater risk of over or under estimation.

The key assumptions for the Earnings Multiple approach are that the selection of comparable companies (chosen on the basis of their business characteristics) and using either historic or forecast revenues provide a reasonable basis for identifying the enterprise value of an investment in determining its fair value. Other assumptions include the appropriateness of the discount applied to the earnings multiple in recognition of the reduced liquidity of the investment.

Investments
Unlisted Investments
Unlisted investments are valued at fair value by the Directors following a detailed review and appropriate challenge of the valuations proposed by the Managers. The Managers' unlisted investment policy applies methodologies consistent with the IPEV guidelines. The principal methodologies applied are market-based approaches and are follows: -

- Earnings Multiple,
- Price of Recent Investment; and
- Net Assets.

The nature of the unlisted portfolio currently will influence the valuation methodology applied.

- the Price of a Recent Investment will be applied only for a limited period (typically up to six months) after the date of acquisition. Generally, after this limited period investments will be valued on the Earnings Multiple basis;
- when valuing on an Earnings Multiple basis, the maintainable earnings of a company are multiplied by an appropriate multiple. An appropriate multiple is sense checked against a basket of recent market transactions. The multiple may be discounted when compared to recent market transactions to reflect the relative size, growth and market segment of the comparable companies;

Figure B2: **Sample PE fund report - Sample valuation**

This figure shows the actual valuation of a portfolio company (FRA) of the fund shown in table B1. Note that, although the value of FRA is computed as the product of EBITDA (£13.3m), percentage of Dunedin's share of net assets (15.1%), and the EBITDA multiple (8.2x), the computed value and the actual valuation show some differences because the EBITDA multiple disclosed in the report is the average multiple applied to all portfolio companies.

FRA

Percentage of equity held	5.4%
Cost of Investment	£6.0m
Directors' valuation	£12.9m
Percentage of Dunedin Enterprise's net assets	15.1%

FRA

Business description
FRA is an international consultancy that provides forensic accounting, data analytics and e-discovery expertise, helping businesses respond to regulatory investigations in an increasingly regulated global environment.

FRA works on some of the largest and most complex regulatory investigations globally. Its clients are typically blue-chip multinational corporates seeking advice to help navigate regulatory scrutiny, effect compliant cross-border data transfer, and manage risk. The company has offices in London, Providence (Rhode Island), Paris, Dallas, New York, Helsinki and Washington DC. It also runs data centres near each office location as well as in Montreal and Zurich.

Investment rationale
FRA services a large and growing global market driven by increasing regulatory activity and scrutiny at an international level. Data volume and complexity is growing rapidly, benefiting FRA in terms of the quantity of data storage, analysis and cross-border data protection rules that must be navigated. FRA's strong organic growth is driven by exceptional client service, a strong reputation among regulators, law firms and corporates, long term engagements and growth in the team of forensic accountants, eDiscovery experts and data analysts.

Value Creation
Regarded as a leading authority in its niche, FRA is seeing demand for its services grow more and more as regulation and enforcement increase globally. The investigation projects are increasingly being supplemented with three-year monitorships of corporations subject to regulatory oversight. Strong relationships with the in-house legal counsel at corporate clients, and with referring law firms, opens up new business opportunities – which FRA is well placed to take advantage of, with its reputation for independence and integrity with regulatory bodies. The strategy is to develop FRA's international reach by recruiting talent into existing offices whilst opening new offices to access further talent pools or expand client relationships.

What has been achieved
The successful expansion of FRA was reliant on accelerating its recruitment drive for talented people around the world, particularly in the US. This was the only way the business would meet ever increasing client demand. Dunedin has helped by getting directly involved in the sourcing and selection process, and filling some of the company's most senior positions. These included a Chairman with global consulting and private equity experience, a Chief Operating Officer and Chief Growth Officer; and two Financial Controllers.

Performance
In the period to 31 December 2017, the EBITDA of FRA was £13.3m on turnover of £39.8m.

Valuations and Gearing
The average earnings multiple applied in the valuation of the Dunedin managed portfolio was 8.2x EBITDA (2017: 7.6x), or 9.4x EBITA (2017: 9.3x). These multiples continue to be applied to maintainable profits.

Within the Dunedin managed portfolio, the weighted average gearing of the companies was 2.7x EBITDA (2017: 3.1x) or 3.1x EBITA (2017: 3.7x).

Analysing the portfolio gearing in more detail, the percentage of investment value represented by different gearing levels was as follows:

Less than 1 x EBITDA	41%
Between 1 and 2 x EBITDA	–%
Between 2 and 3 x EBITDA	11%
More than 3 x EBITDA	48%

Appendix C Proxies of earnings management

In this section, I discuss the measures used to proxy earnings management. In this paper, I employ both REM and AEM, for two reasons. First, AEM could be used to accelerate (delay) recognition of revenue (expenses), both important for increasing firm performance. In addition, AEM may be a less costly way to inflate firm performance because it does not affect firm fundamentals (Dechow et al., 2010).

Second, GPs can exert pressure to the operational activities of the portfolio firms, and REM captures these activities well. Gompers et al. (2016)'s survey reveals that GPs consider "operational improvements" of portfolio firms as one of the most important drivers of fund returns,[29] and that the GPs find "revenue/demand increases" as the most important value-add which the GPs contribute to the portfolio firms.[30]

Third, both AEM and REM could occur in portfolio firms because the combination would be difficult to detect than using only one of the two methods. For instance, Kothari, Mizik, and Roychowdhury (2016) find that, markets fail to detect earnings management only when it is backed by REM; Cohen and Zarowin (2010) and Zang (2012) demonstrate that firms that are under greater scrutiny by auditors engage in REM more than accruals management. Because most LPs, who invest in PE funds are sophisticated (Acharya, Gottschalg, Hahn, and Kehoe, 2013; Da Rin and Phalippou, 2017), GPs may prefer ways to use ways that are more difficult for the sophisticated investors to detect.

C.1 Accrual earnings management

To measure AEM, I use the modified Jones model, by estimating the following modified-Jones accruals regression for each country, industry (two-digit SIC) and year, using the entire Amadeus dataset from 2000 to 2017. I require each regression observations to be larger than ten.

$$\frac{TAcc_{i,t}}{A_{i,t-1}} = \alpha_0 + \alpha_1\left(\frac{1}{A_{i,t-1}}\right) + \alpha_2\left(\frac{PPE_{i,t}}{A_{i,t-1}}\right) + \alpha_3\left(\frac{\Delta S_{i,t}}{A_{i,t-1}}\right) + \alpha_4 ROA_{i,t} + \varepsilon_{i,t} \tag{C.1}$$

where $TAcc_{i,t}$ is total accruals of firm i at year t; $PPE_{i,t}$ is property, plant and equipment of firm i at year t; $ROA_{i,t}$ is ROA of firm i at year t. The measure becomes my variable of interest, abnormal accruals. Note that, I use the cash method (despite the findings in Hribar and Collins (2002)) to obtain total accruals because cash flow statement data in Amadeus is extremely scarce.

C.2 Real earnings management

I use Roychowdhury (2006)'s REM measures (abnormal production costs, abnormal discretionary expenses) as proxies of REM. To obtain the measures, I estimate the following equations for each country-industry-year.

[29] 97.1% of the respondents answered operational improvements as an important driver of returns.

[30] 70.3% of the respondents responded that GPs can add value to portfolio firms by increasing revenue or by improving demand.

To obtain abnormal discretionary expenses, I regress the following:

$$\frac{Disexp_{i,t}}{A_{i,t-1}} = \alpha_0 + \alpha_1(\frac{1}{A_{i,t-1}}) + \alpha_2(\frac{S_{i,t-1}}{A_{i,t-1}}) + \rho_{i,t} \tag{C.2}$$

where $\frac{Disexp_{i,t}}{A_{i,t-1}}$ denotes *normal* discretionary expenses, which is operating expenses; $\frac{S_{i,t-1}}{A_{i,t-1}}$ indicates lagged sales.[31] Both variables are scaled by lagged total assets. $\rho_{i,t}$ indicates the abnormal discretionary expenses after estimating this regression. To obtain abnormal production costs, I estimate the following:

$$\frac{Prod_{i,t}}{A_{i,t-1}} = \alpha_0 + \alpha_1(\frac{1}{A_{i,t-1}}) + \alpha_2(\frac{S_{i,t}}{A_{i,t-1}}) + \alpha_3(\frac{\Delta S_{i,t}}{A_{i,t-1}}) + \alpha_4(\frac{\Delta S_{i,t-1}}{A_{i,t-1}}) + \lambda_{i,t} \tag{C.3}$$

where $\frac{Prod_{i,t}}{A_{i,t-1}}$ is *normal* production costs, which adds cost of good sold and changes in inventory; $\frac{1}{A_{i,t-1}}$ is the inverse of lagged total assets; $\frac{S_{i,t}}{A_{i,t-1}}$ denotes sales; $\frac{\Delta S_{i,t}}{A_{i,t-1}}$ denotes changes in sales; $\frac{\Delta S_{i,t-1}}{A_{i,t-1}}$ is *lagged* changes in sales. All variables are scaled by lagged total assets. $\lambda_{i,t}$ denotes the abnormal production costs after estimating this regression.

C.3 Country-industry-year-level regression results

Table C1 presents country-industry-year level regression results. Columns (1), (2), (3), and (4) present results for regressions obtaining abnormal accruals, discretionary sales, abnormal production costs, and abnormal discretionary expenses, respectively. Columns (1), (2), (3), and (4) have Mean number of observations per group (country-industry-year) is 1,242, 1,670, 467, and 607, respectively; mean adjusted R-squared is 0.277, 0.189, 0.819, and 0.380, respectively. The differences in number of observations throughout the estimation model is due to the heterogeneity of income statement data across different firms. EU firms have different financial statement disclosure requirements across different size thresholds (e.g., Bernard, Burgstahler, and Kaya, 2018; Breuer, 2021).

C.4 Performance-matching

Across all variables, I conduct performance-matching using two steps, following Kothari et al. (2005). First, for each firm-year i, t, I identify another firm-year j, t within the same country-industry (SIC two-digit) that has closest ROA with firm-year i, t. Then, I subtract EM of firm-year j, t from EM of firm i, t. This becomes the final performance-matched measure.

[31] Roychowdhury (2006) uses lagged sales to estimate abnormal discretionary expenses, because abnormal discretionary expenses can be unusually low (even if managers do not engage in reducing discretionary expenses), if managers decide to manage sales upward.

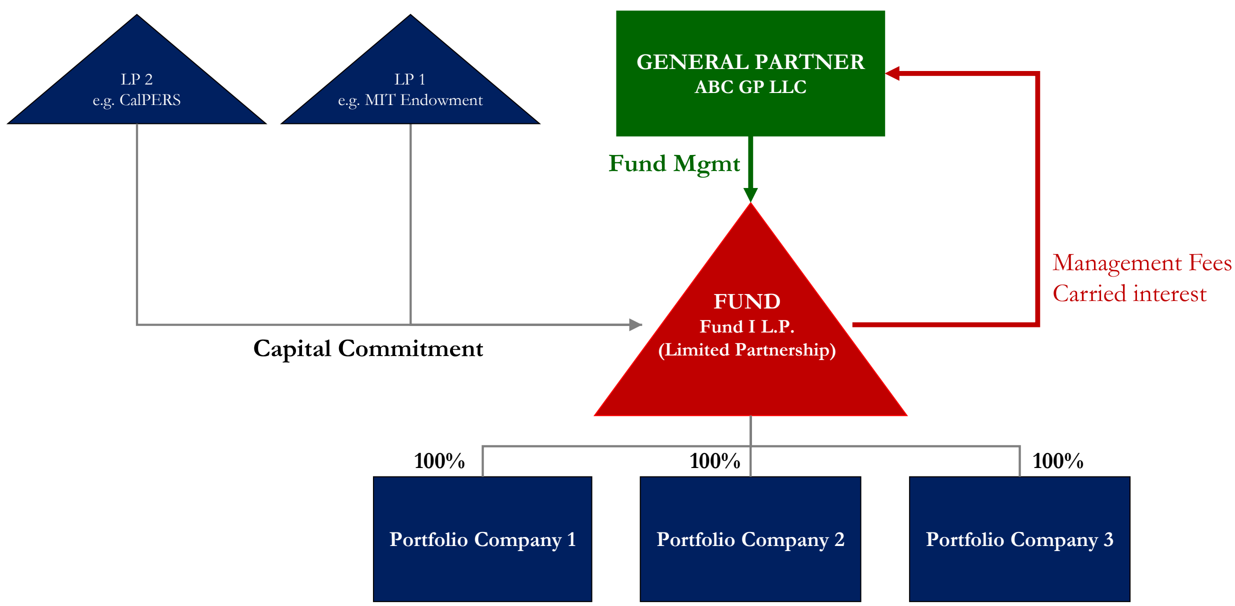
Table C1: **Country-industry-year level regression results**

	(1) Accruals	(2) Prod Cost	(3) Disc. Exp
$1/A_{t-1}$	1,971.8	24,739.854	-180,830.569
	(0.01)	(0.02)	(-0.13)
$\Delta S_t/A_{t-1}$	0.058	-0.427	
	(0.74)	(-0.25)	
$\Delta S_{t-1}/A_{t-1}$		-0.444	
		(-0.37)	
PPE_t/A_{t-1}	-0.355*		
	(-1.86)		
NI_t/A_{t-1}	0.351		
	(1.60)		
$Sales_t/A_{t-1}$		0.869	
		(0.69)	
$Sales_{t-1}/A_{t-1}$			-121.569***
			(-1,269.23)
Constant	0.009	0.175	133.630***
	(0.15)	(1.04)	(694.15)
Mean N	1,242	467	603
Mean Adj. R-sq	0.277	0.819	0.380
# of groups		56,524	

Figure 1: **PE fund structure and fund life-cycle**

This figure presents the structure and the life-cycle of a typical private equity fund. Panel A presents a typical PE fund structure. "General Partners" (green box) are PE managers (e.g., KKR, Carlyle), who manage the fund and receive annual management fees (typically 2% of committed capital) and a performance fee (normally 20% of investment returns); "LPs" provide capital to the fund, which consists of pension funds (e.g., MIT Endowment fund), insurance companies, and high net worth individuals. "Fund" (red triangle) denotes the PE *fund* which the LPs commit capital to (e.g., Carlyle Partners III L.P.). "Portfolio Companies" (navy box) denote portfolio companies which the Fund invests in (e.g., Dell, RJR Nabisco and many others). GPs monitor the Portfolio Companies.

Panel A: PE fund structure



Panel B: PE fund life-cycle

Panel B reports a typical PE fund life-cycle. “Fund I” denotes the first fund a GP has raised. “Fund II” is the second fund the GP has raised. “Year” denotes the relative year since the inception of the first fund. “Fundraise close” is the final securing of additional funds. “Fundraising” denotes the fundraising period, whereby GPs meet potential investors of the fund and promotes their new fund to them. “Investment phase” is defined as the phase where GPs find targets and invests in portfolio firms. This phase can typically range from 3-5 years since fund close. “Divestment phase” denotes the period where the GPs are monitoring portfolio companies and exiting them. The box “Performance Management” (red text) is where NAV inflation is likely to occur, and is the period defined as FundraiseFlag period in my sample. In this case, since the GPs already own portfolio firms from Fund I, they have the opportunity to manage earnings and may attempt to do so.

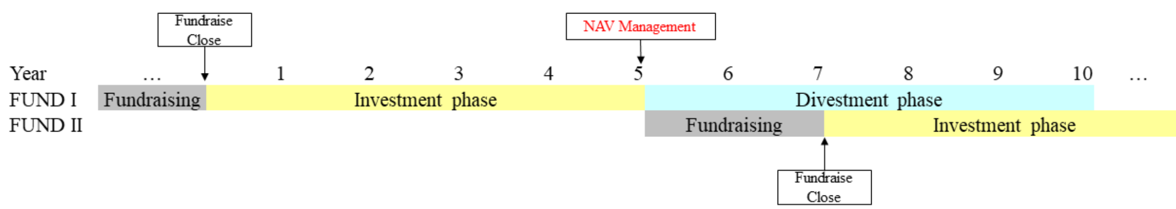


Figure 2: **Valuation numerical example**

This figure shows a numerical example of NAV calculation. The red triangle denotes an exemplary fund named CVC Capital Partners V ("the Fund"); navy boxes represent portfolio firms invested by the Fund. For each portfolio firm, EBITDA is multiplied by the EV/EBITDA multiple to obtain each portfolio firm's valuation. Assuming the Fund's 100% ownership in these investments, the sum of the values ($900m + $400m + $2.5bn), $3.8bn, is the NAV of the Fund at a given quarter.

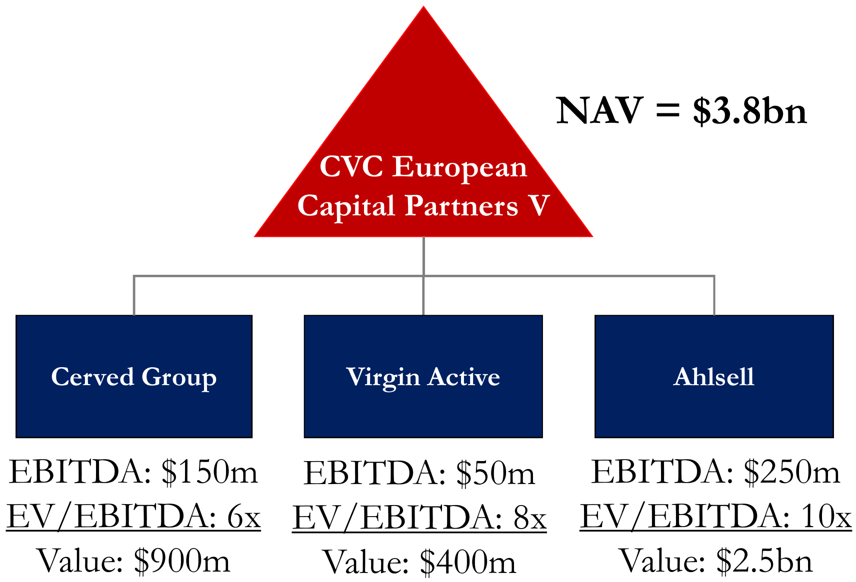
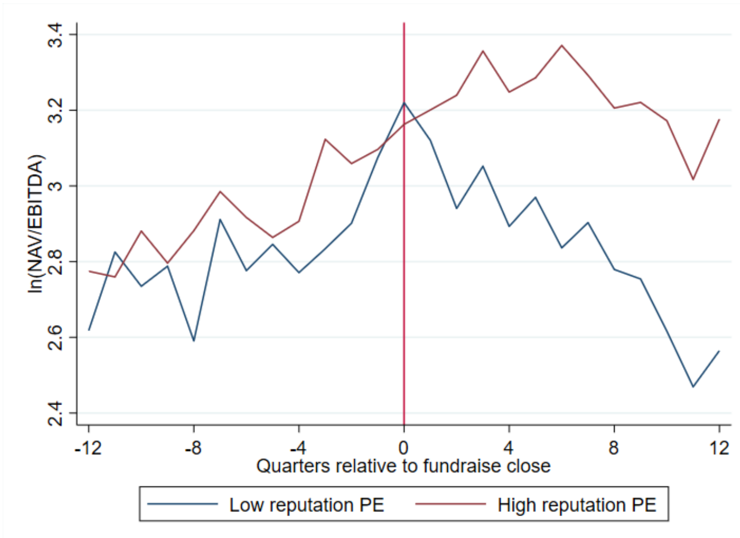


Figure 3: **Valuation multiples pre-post fundraising**

This figure plots mean values of EBITDA (Panel A) and sales (Panel B) multiples before and after fundraising periods. The X axis shows the quarters relative to fundraise close (quarter 0), and the Y axis shows the mean values of natural log of NAV divided by sum of EBITDA or sales for each fund quarter. Blue line (red line) depicts values for low (high) reputation GPs.

Panel A: EBITDA multiple



Panel B: Sales multiple

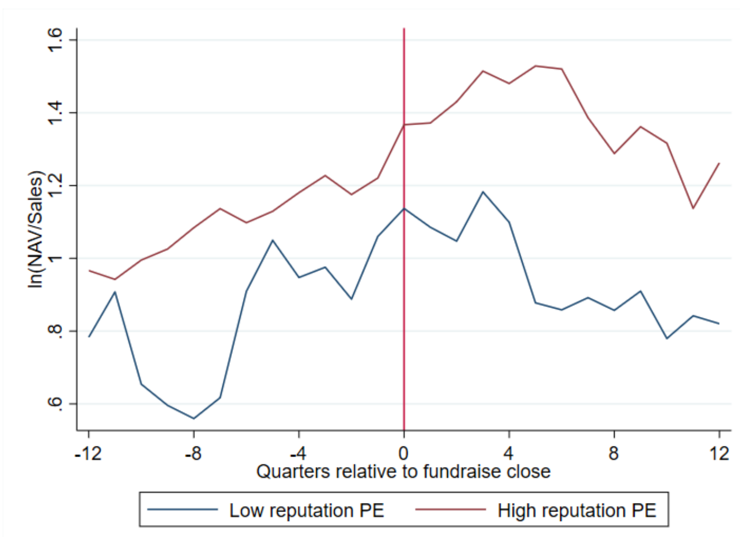
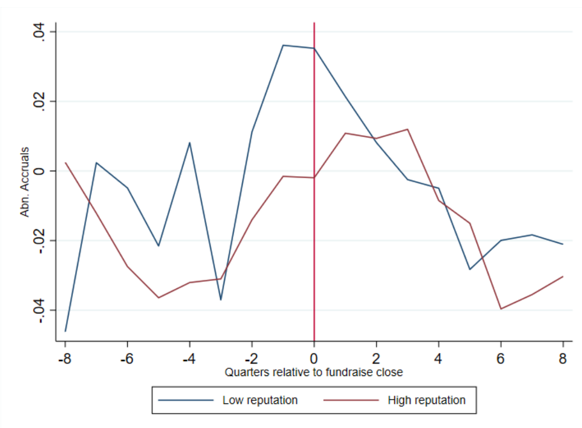


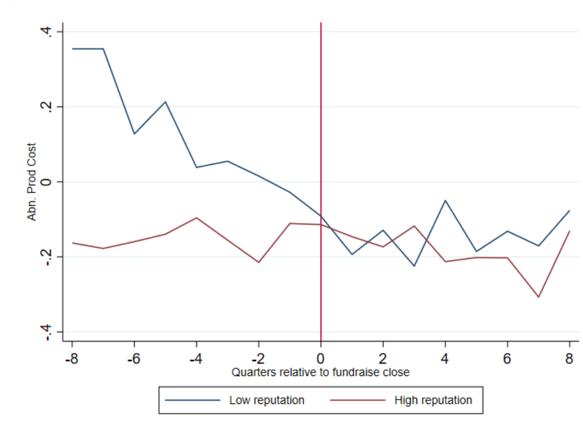
Figure 4: **Earnings management pre-post fundraising**

This figure plots mean values of abnormal accruals (Panel A) and abnormal production costs (Panel B), and abnormal discretionary expenses (Panel C) before and after fundraising periods. The X axis shows the quarters relative to fundraise close (quarter 0), and the Y axis shows the mean values of earnings management variables for each fund quarter. Blue line (red line) reputation values for low (high) reputation GPs.

Panel A: Abnormal accruals



Panel B: Abnormal production cost



Panel C: Abnormal discretionary expenses

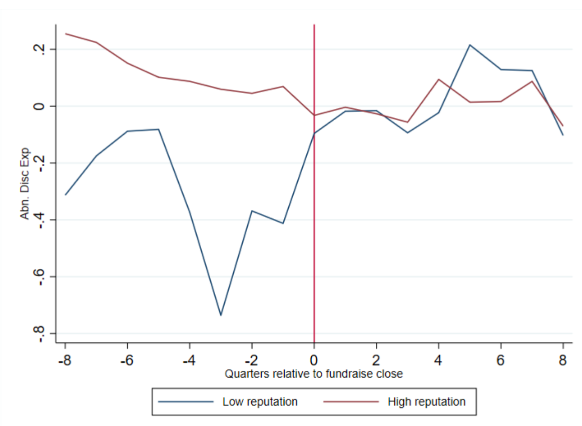


Table 1: **Sample countries and characteristics**

Panel A shows a list of GP and portfolio firm countries; Panel B shows descriptive statistics of the funds. See Table A1 for variable definitions.

Panel A: Funds by GP country

Country	GP	%	Portfolio firms	%
UK	117	28.5%	637	34.7%
France	18	4.4%	275	15.0%
Netherlands	15	3.7%	12	0.7%
Sweden	13	3.2%	227	12.4%
Finland	8	2.0%	81	4.4%
Italy	5	1.2%	132	7.2%
Germany	3	0.7%	136	7.4%
Spain	3	0.7%	80	4.4%
Denmark	3	0.7%	46	2.5%
US	185	45.1%	0	0%
Other countries	225	54.9%	212	11.5%
Total	410	100.0%	1,838	100.0%

Panel B: Fund characteristics

GP Reputation	Stats	N	Mean	SD	p25	p50	p75
All funds	Fund Size (US$ m)	410	2,903.772	3,694.071	558.000	1,431.975	3,677.300
	Fund #	410	5.420	2.887	3.000	5.000	8.000
	Vintage	410	2009.276	5.293	2006	2009	2014
Low reputation	Fund Size (US$ m)	102	897.390	1,071.508	265.150	471.395	1,200.000
	Fund #	102	2.559	1.480	2	2	3
	Vintage	102	2,007.529	5.464	2005	2007	2012
High reputation	Fund Size (US$ m)	308	3,568.224	4,002.740	828.655	2,060.850	4,837.605
	Fund #	308	6.367	2.600	4	6	9
	Vintage	308	2009.854	5.114	2006	2011	2014

Table 2: **Fund-level descriptive statistics**

Panel A provides summary statistics of the entire fund-level sample; Panel B shows the means and their differences for funds managed by high and low reputation GPs. Continuous variables are winsorized at 1% (valuation multiple variables are winsorized at 5%). See Table A1 for variable definitions. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Sample descriptive statistics

Variable	N	Mean	SD	p25	p50	p75
FundraiseFlag	8,709	0.112	0.316	0.000	0.000	0.000
NAV/Sales	8,709	9.488	15.011	0.629	2.213	9.240
NAV/EBITDA	8,699	35.576	56.939	2.975	12.441	46.239
ln(NAV/Sales)	8,709	0.879	1.815	(0.464)	0.794	2.224
ln(NAV/EBITDA)	7,800	2.685	1.766	1.626	2.755	4.037
ln(# of Pf Firms)	8,709	1.652	0.759	1.099	1.609	2.197
ln(Fund Age)	8,709	1.742	0.624	1.386	1.792	2.197
ln(GP Age)	8,709	3.036	0.665	2.708	3.178	3.434

Panel B: Mean values by fund's GP reputation

	Low reputation		High reputation		
Variables	N	Mean (1)	N	Mean (2)	(1) - (2)
FundraiseFlag	2,317	0.101	6,392	0.116	-0.016**
NAV/Sales	2,317	6.557	6,392	10.550	-3.993***
NAV/EBITDA	2,317	26.182	6,382	38.986	-12.804***
ln(NAV/Sales)	2,317	0.545	6,392	1.001	-0.456***
ln(NAV/EBITDA)	2,018	2.406	5,782	2.783	-0.377***
ln(# of Pf Firms)	2,317	1.465	6,392	1.720	-0.256***
ln(Fund Age)	2,317	1.860	6,392	1.699	0.162***
ln(GP Age)	2,317	2.703	6,392	3.157	-0.454***

Table 3: **Portfolio firm-level descriptive statistics**

Panel A provides summary statistics of the entire portfolio firm-level sample; Panel B shows the means and their differences for portfolio firms under high and low reputation GPs. All continuous variables are winsorized at 1%. See Table A1 for variable definitions. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Sample descriptive statistics

Variables	N	Mean	SD	p25	p50	p75
Abn. Accruals	18,362	-0.008	0.275	-0.089	0.000	0.063
Abn. Prod Cost	9,683	0.064	1.241	-0.165	0.000	0.321
Abn. Disc Exp	26,328	0.119	0.324	0.000	0.000	0.000
Inverse TA	26,328	0.000	0.000	0.000	0.000	0.000
Leverage	26,328	0.727	0.605	0.488	0.689	0.859
ROA	26,328	0.041	0.232	-0.015	0.040	0.123
Chg Sales	26,328	0.097	0.461	-0.012	0.042	0.194

Panel B: Mean values by fund's GP reputation

	Low reputation		High reputation		
Variables	N	Mean (1)	N	Mean (2)	(1) - (2)
Abn. Accruals	3,652	0.001	14,710	-0.010	0.012**
Abn. Prod Cost	1,267	-0.035	4,278	-0.145	0.110***
Abn. Disc Exp	2,263	-0.080	7,420	0.108	-0.188***
FundraiseFlag	4,880	0.110	21,448	0.121	-0.011**
Inverse TA	4,880	0.000	21,448	0.000	-0.000**
Leverage	4,880	0.689	21,448	0.736	-0.047***
ROA	4,880	0.035	21,448	0.042	-0.008**
Chg Sales	4,880	0.070	21,448	0.103	-0.032***

Table 4: **Increases in fund valuation multiples**

This table presents estimates of the following regression (Equation 1):

$$\ln\left(\frac{NAV_{i,t}}{\sum_{j=1}^{n} Performance_{j,t-1}}\right) = \beta_1 FundraiseFlag_{i,t} + \gamma' X_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t}$$

Panel A (Panel B) presents regression results using low reputation (high reputation) GPs. Columns (1) and (2) ((3) and (4)) use the entire sample (entropy-balanced sample).See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level (valuation multiple variables are winsorized at 5%). *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Low reputation GPs

	Main sample		Entropy-balanced sample	
	(1)	(2)	(3)	(4)
Dependent var:	ln(NAV/EBITDA)	ln(NAV/Sales)	ln(NAV/EBITDA)	ln(NAV/Sales)
FundraiseFlag	0.182*	0.227**	0.157**	0.170*
	(1.78)	(1.98)	(2.06)	(1.87)
Controls	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
N	2,018	2,317	1,371	1,590
R-sq	0.792	0.761	0.891	0.876
Clustering	Fund	Fund	Fund	Fund
SUR Tests				
χ^2 vs. Panel B	6.36**	5.69**	18.19***	23.57***
Prob > χ^2	0.012	0.017	0.000	0.000

Panel B: High reputation GPs

	Main sample		Entropy-balanced sample	
	(1)	(2)	(3)	(4)
Dependent var:	ln(NAV/EBITDA)	ln(NAV/Sales)	ln(NAV/EBITDA)	ln(NAV/Sales)
FundraiseFlag	-0.119*	-0.070	-0.127*	-0.115*
	(-1.83)	(-1.30)	(-1.89)	(-1.95)
Controls	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
N	5,782	6,392	4,804	5,295
R-sq	0.766	0.813	0.825	0.868
Clustering	Fund	Fund	Fund	Fund

Table 5: **Portfolio firm-level earnings management**

This table presents estimates of the following regression (Equation 2):

$$EM_{i,j,t-1} = \beta_1 FundraiseFlag_{i,t} + \gamma' X_{i,j,t-1} + \alpha_i + \alpha_t + \alpha_j + \alpha_{c,ind,t-1} + \epsilon_{i,j,t-1}$$

where coefficient β_1 is the coefficient of interest. Panel A (Panel B) presents regression results using low reputation (high reputation) GPs. Columns (1), (2), and (3) ((4), (5), and (6)) use the entire sample (entropy-balanced sample). See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Low reputation GPs

	Main sample			Entropy-balanced sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
FundraiseFlag	0.038*	0.143*	-0.071	0.019	0.142**	-0.239*
	(1.95)	(1.81)	(-0.47)	(1.57)	(2.45)	(-1.67)
Controls	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Pf Firm FE	Y	Y	Y	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y	Y	Y	Y
N	3,653	1,267	2,263	2,414	888	1,687
R-sq	0.804	0.843	0.661	0.952	0.950	0.786
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY
SUR Tests						
χ^2 vs. Panel B	3.50*	2.68	0.00	5.49**	21.00***	7.15***
Prob > χ^2	0.061	0.101	0.947	0.019	0.000	0.008

Panel B: High reputation GPs

	Main sample			Entropy-balanced sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
FundraiseFlag	-0.002	-0.021	-0.062	-0.002	-0.047	-0.057
	(-0.13)	(-0.31)	(-1.11)	(-0.19)	(-1.05)	(-0.87)
Controls	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Pf Firm FE	Y	Y	Y	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y	Y	Y	Y
N	14,787	4,293	7,451	12,503	3,707	6,544
R-sq	0.594	0.564	0.498	0.746	0.802	0.624
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY

Table 6: **Falsification test using VC and multiple investors**

This table shows the results estimating Equation 2 using a sample of venture capital transactions and buyout transactions with multiple (more than two) investors. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent var: Abn.	(1) Accruals	(2) Prod Cost	(3) Disc Exp
FundraiseFlag	-0.078	-0.079	-0.134
	(-1.48)	(-0.96)	(-0.60)
Controls	Y	Y	Y
Fund FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Pf Firm FE	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y
N	2,915	930	1,764
R-sq	0.772	0.843	0.741
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY

Table 7: **Effects of PE ownership**

This table presents estimates of the following regression (Equation 3):

$$EM_{i,j,t-1} = \beta_1 PEOwn_{i,j,t-1} + \gamma' X_{i,j,t-1} + \alpha_i + \alpha_t + \alpha_j + \alpha_{c,ind,t-1} + \alpha_{i,j,t-1}$$

where coefficient β_1 is the coefficient of interest. The table shows results for low reputation (columns (1)-(3)) and high reputation (columns (4)-(6)) GP portfolio firms. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Low reputation			High reputation		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
PEOwn	-0.005	0.107	-0.011	-0.016*	-0.084*	0.050
	(-0.23)	(1.07)	(-0.19)	(-1.81)	(-1.87)	(0.84)
Controls	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Pf Firm FE	Y	Y	Y	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y	Y	Y	Y
N	6,167	2,148	3,691	31,986	9,197	16,550
R-sq	0.484	0.517	0.374	0.378	0.425	0.455
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY

Table 8: **Removing firm-years close to exit**

This table presents estimates of Equation 2, after removing portfolio firm-years less than two calendar years apart from the exit year. The table shows results only for low reputation GP portfolio firms. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent var: Abn.	(1) Accruals	(2) Prod Cost	(3) Disc Exp
FundraiseFlag	0.029	0.155**	-0.079
	(1.44)	(2.16)	(-0.51)
Controls	Y	Y	Y
Fund FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Pf Firm FE	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y
N	3,570	1,230	2,198
R-sq	0.805	0.856	0.670
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY

Table 9: **NAV management strategy and fundraising outcomes**

This table tests the fundraising outcomes according to each NAV management strategy (i.e., valuation multiples and earnings management). Specifically, for each sample, I keep only fundraising quarters and take the mean of valuation multiples (Panel A) and earnings management (Panel B), and conduct the following regression (Equation 4):

$$\begin{aligned} Finalfund_i = &\beta_1 MeanMultiple_i(MeanEM_i) \times FundraiseFlag_i + \beta_2 MeanMultiple_i \\ &+ \beta_3 FundraiseFlag_i + \gamma' X_i + \alpha_c + \alpha_v + \alpha_y + \alpha_i \end{aligned}$$

See Table A1 for complete list of variable definitions. Continuous variables are winsorized at the 1% level (valuation multiple variables are winsorized at 5%). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund-level sample

	Low reputation		High reputation	
	(1)	(2)	(3)	(4)
Dependent var:	Finalfund	Finalfund	Finalfund	Finalfund
ln(NAV/EBITDA) × FundraiseFlag	0.052*		0.010	
	(1.84)		(0.94)	
ln(NAV/EBITDA)	-0.056***		-0.028*	
	(-2.67)		(-1.76)	
ln(NAV/Sales) × FundraiseFlag		0.043**		0.014
		(1.96)		(1.56)
ln(NAV/Sales)		-0.047**		-0.034**
		(-2.49)		(-2.01)
FundraiseFlag	-0.217***	-0.099*	-0.089**	-0.063**
	(-2.80)	(-1.72)	(-2.06)	(-2.08)
Controls	Y	Y	Y	Y
Vintage FE	Y	Y	Y	Y
GP Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	153	162	469	493
R-sq	0.775	0.760	0.394	0.397
Clustering	Fund	Fund	Fund	Fund

Panel B: Portfolio firm-level

	Low reputation			High reputation		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var:	Finalfund	Finalfund	Finalfund	Finalfund	Finalfund	Finalfund
Abn. Accruals × FundraiseFlag	-0.588*			0.006		
	(-1.84)			(0.05)		
Abn. Accruals	0.242			0.099		
	(1.38)			(0.91)		
Abn. Prod Cost × FundraiseFlag		0.124			0.033	
		(0.21)			(0.70)	
Abn. Prod Cost		-0.114			0.001	
		(-0.50)			(0.03)	
Abn. Disc Exp × FundraiseFlag			0.016			-0.015
			(0.61)			(-0.63)
Abn. Disc Exp			-0.026			-0.011
			(-0.71)			(-0.46)
FundraiseFlag	-0.087	-0.144	-0.078	-0.074*	-0.107	-0.067
	(-1.34)	(-0.58)	(-0.90)	(-1.75)	(-1.64)	(-1.46)
Controls	Y	Y	Y	Y	Y	Y
Vintage FE	Y	Y	Y	Y	Y	Y
GP Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	134	64	84	422	266	323
R-sq	0.722	0.960	0.961	0.412	0.444	0.351
Clutering	GP	GP	GP	GP	GP	GP

Internet Appendix for:

Private equity fund valuation management during fundraising

Brian K. Baik

Figure IA1: **Number of funds by vintage**

This figure plots the number of funds by vintage. My sample consists of buyout funds from vintages 1996 to 2018. See Table A1 for a list of variable definitions related to private equity.

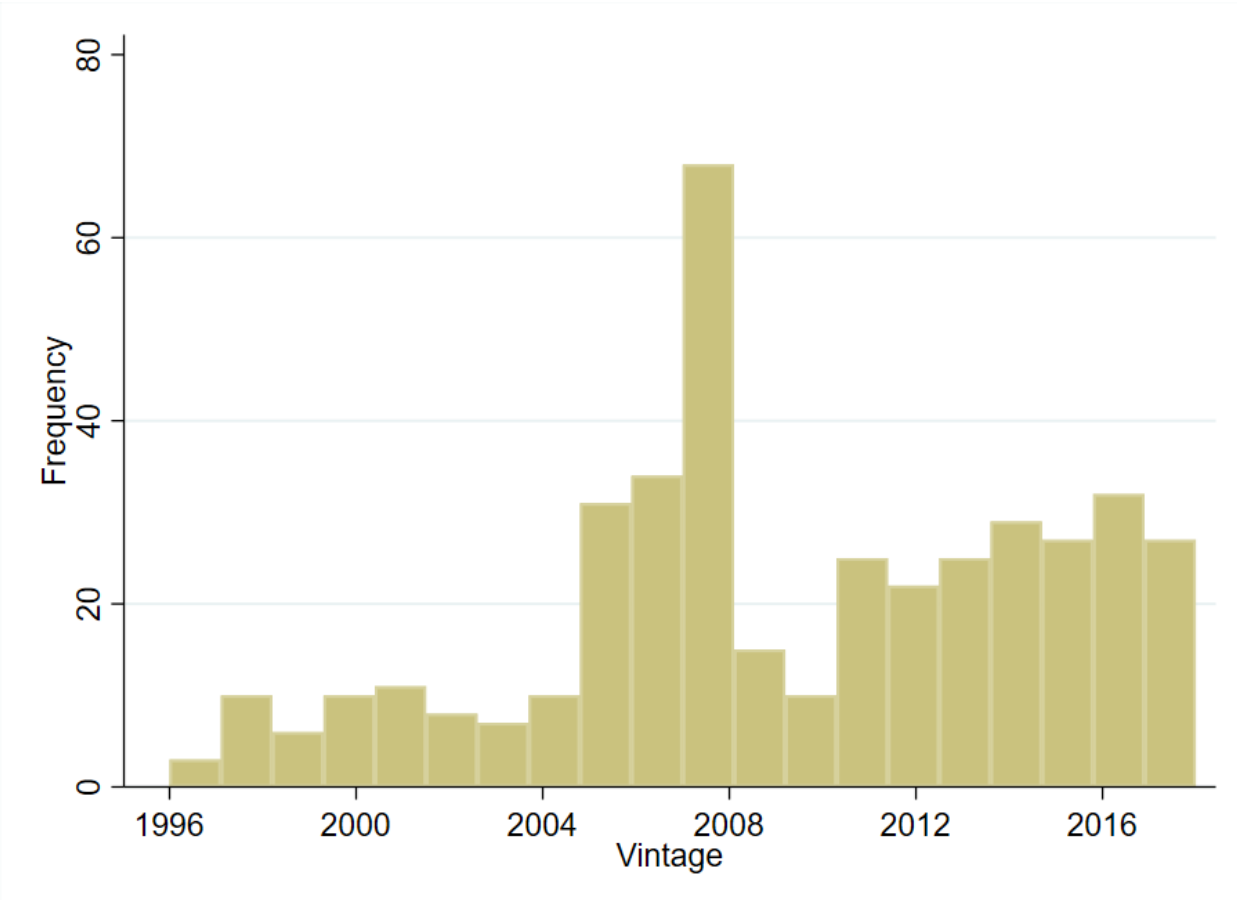


Table IA1: **Alternative definitions of fund reputation**

This table uses an alternative definition of fund reputation and re-estimates Equation 1 (Panel A) and Equation 2 (Panel B), where coefficient β_1 is the coefficient of interest. In Panel A, columns (1)-(2) ((3)-(4)) report results for funds owned by low (high) reputation GPs; in Panel B, columns (1)-(3) ((4)-(6)) report results for portfolio firms owned by low (high) reputation GPs. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level (valuation multiple variables are winsorized at 5%). *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund-level tests

GP Type	Alt. low reputation		Alt. high reputation	
	(1)	(2)	(3)	(4)
Dependent var:	ln(NAV/EBITDA)	ln(NAV/Sales)	ln(NAV/EBITDA)	ln(NAV/Sales)
FundraiseFlag	0.107	0.141	-0.123*	-0.057
	(1.09)	(1.52)	(-1.76)	(-0.97)
Fund FE	Y	Y	Y	Y
Year x Quarter FE	Y	Y	Y	Y
N	2,411	2,789	5,389	5,920
R-sq	0.788	0.779	0.764	0.808
Clustering	Fund	Fund	Fund	Fund

Panel B: Portfolio firm-level tests

GP Type	Alternative low reputation			Alternative high reputation		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
FundraiseFlag	0.011	0.262*	-0.242	0.002	-0.053	-0.040
	(0.39)	(1.91)	(-1.44)	(0.13)	(-0.76)	(-0.50)
Controls	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Pf Firm FE	Y	Y	Y	Y	Y	Y
Pf Firm Country-Year FE	Y	Y	Y	Y	Y	Y
N	5,076	1,633	2,806	13,364	3,927	6,908
R-sq	0.730	0.746	0.566	0.599	0.575	0.522
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY

Table IA2: **Using cash-flow based fundraise flag**

This table uses subsequent fund's first cash flow date as fundraise close date and re-estimates Equation 1 (Panel A) and Equation 2 (Panel B). In Panel A, columns (1)-(2) ((3)-(4)) report results for funds owned by low (high) reputation GPs; in Panel B, columns (1)-(3) ((4)-(6)) report results for portfolio firms owned by low (high) reputation GPs. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level (valuation multiple variables are winsorized at 5%). *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund-level tests

	Low reputation		High reputation	
	(1)	(2)	(3)	(4)
Dependent var:	ln(NAV/EBITDA)	ln(NAV/Sales)	ln(NAV/EBITDA)	ln(NAV/Sales)
FundraiseFlag_CF	0.214*	0.335*	-0.083	-0.007
	(1.74)	(1.86)	(-0.97)	(-0.10)
Fund FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
N	2,018	2,317	5,782	6,392
R-sq	0.792	0.761	0.765	0.812
Cluster	Fund	Fund	Fund	Fund

Panel B: Portfolio firm-level tests

	Low reputation			High reputation		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var: Abn.	Accruals	Prod Costs	Disc Exp	Accruals	Prod Costs	Disc Exp
FundraiseFlag_CF	0.039	0.136	-0.200	-0.008	0.020	-0.010
	(1.47)	(1.53)	(-0.80)	(-0.47)	(0.21)	(-0.13)
Fund FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Pf Firm FE	Y	Y	Y	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y	Y	Y	Y
N	3,652	1,267	2,263	14,710	4,278	7,420
R-sq	0.803	0.843	0.643	0.596	0.566	0.520
Clustering	Fund, Pf Firm CIY	Fund, Pf Firm CIY	Fund, Pf Firm CIY	Fund, Pf Firm CIY	Fund, Pf Firm CIY	Fund, Pf Firm CIY

Table IA3: **Winsorization at 1% level**

This table uses the dependent variable in Equation 1 winsorizing at the 1% level instead of 5%. Columns (1)-(2) ((3)-(4)) use low reputation (high reputation) GP samples. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level (valuation multiple variables are winsorized at 5%). *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Low reputation		High reputation	
	(1)	(2)	(3)	(4)
Dependent var:	ln(NAV/EBITDA)	ln(NAV/Sales)	ln(NAV/EBITDA)	ln(NAV/Sales)
FundraiseFlag	0.200	0.350	-0.076	-0.099
	(1.50)	(1.57)	(-0.75)	(-1.41)
Fund FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
N	2,018	2,317	5,782	6,392
R-sq	0.756	0.675	0.762	0.784
Cluster	Fund	Fund	Fund	Fund

Table IA4: **Non performance-matched earnings management measures as dependent variable**

This table reports regression results using non performance-matched earnings management proxies as dependent variables and re-estimate Equation 2. The table reports results for portfolio firms owned by low reputation GPs. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Dependent variable: Abn.	Accruals	Prod Cost	Disc Exp
FundraiseFlag	0.026*	0.013	-0.073**
	(1.73)	(0.46)	(-2.09)
Controls	Y	Y	Y
Fund FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Pf Firm FE	Y	Y	Y
Pf Firm Country-Year FE	Y	Y	Y
N	5,176	2,303	3,119
R-sq	0.637	0.978	0.903
Clustering	Fund, Pf firm	Fund, Pf firm	Fund, Pf firm

Table IA5: **Random fundraise dates**

This table re-estimates Equation 1 (Panel A) and Equation 2 (Panel B) 100 times using randomly generated fundraise flag dates (variable *FundraiseFlag_Rand*). The reported coefficients and standard errors are the mean of the 100 iterations, using the low reputation GP sample. Panel A (Panel B) shows the results for fund-level (portfolio firm-level) sample. The row "<10% sig with pr. Sign" shows the number of iterations (out of 100 for each column) that produced statistically significant (<10%) results with the same predicted sign. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level (valuation multiple variables are winsorized at 5%). *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund level

Dependent var:	(1) ln(NAV/EBITDA)	(2) ln(NAV/Sales)
FundraiseFlag_Rand	0.005	-0.004
	(0.08)	(-0.07)
<10% sig with pr. Sign	6/100	3/100
Controls	Y	Y
Fund FE	Y	Y
Year x Quarter FE	Y	Y
N	2,018	2,317
R-sq	0.791	0.759
Clustering	Fund	Fund

Panel B: Portfolio-firm level

Dependent var: Abn.	(1) Accruals	(2) Prod Cost	(3) Disc Exp
FundraiseFlag_Rand	-0.002	0.003	-0.013
	(-0.24)	(0.06)	(-0.14)
<10% sig with pr. Sign	6/100	9/100	6/100
Controls	Y	Y	Y
Fund FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Pf Firm FE	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y
N	3,653	1,267	2,263
R-sq	0.802	0.842	0.661
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY

Table IA6: **Entropy balancing - fund-level**

This table presents results for entropy balancing procedure at the fund-level (Regression results from Table 4). Panel A (Panel B) reports entropy balancing results for low reputation (high reputation) GP sample. Each reputation sample is matched to have similar first and second moments between treated (Fundraiseflag=1) and control (FundraiseFlag=0) groups.

Panel A: Low reputation GPs

Before entropy balancing	Treat		Control	
Variables	Mean	Variance	Mean	Variance
ln(Fund Age)	1.627	0.127	1.975	0.307
NAV	0.742	0.052	0.494	0.098
ln(Fund size)	6.415	1.040	6.587	0.976
Cum. Distribution	0.303	0.087	0.883	0.495
Fundraise year	2011	12.320	2010	21.560
After entropy balancing	Treat		Control	
	Mean	Variance	Mean	Variance
ln(Fund Age)	1.627	0.127	1.627	0.127
NAV	0.742	0.052	0.741	0.052
ln(Fund size)	6.415	1.040	6.414	1.040
Cum. Distribution	0.303	0.087	0.304	0.088
Fundraise year	2011	12.320	2011	12.330

Panel B: High reputation GPs

Before entropy balancing	Treat		Control	
	Mean	Variance	Mean	Variance
ln(Fund Age)	1.349	0.238	1.802	0.379
NAV	0.633	0.075	0.537	0.108
ln(Fund size)	7.822	1.337	7.892	1.417
Cum. Distribution	0.196	0.071	0.723	0.519
Fundraise year	2012	27.670	2010	31.860
After entropy balancing	Treat		Control	
	Mean	Variance	Mean	Variance
ln(Fund Age)	1.349	0.238	1.349	0.238
NAV	0.633	0.075	0.633	0.075
ln(Fund size)	7.822	1.337	7.822	1.337
Cum. Distribution	0.196	0.071	0.196	0.071
Fundraise year	2012	27.670	2012	27.670

Table IA7: **Entropy balancing - portfolio firm-level)**

This table presents results for entropy balancing procedure at the portfolio firm-level (Regression results from Table 5). Panel A (Panel B) reports entropy balancing results for low reputation (high reputation) GP sample. Each reputation sample is matched to have similar first and second moments between treated (Fundraiseflag=1) and control (FundraiseFlag=0) groups.

Panel A: Low reputation GPs

Before entropy balancing	Treat		Control	
Variables	Mean	Variance	Mean	Variance
ln(Fund Age)	1.643	0.122	2.044	0.285
NAV	0.729	0.046	0.491	0.121
ln(Fund size)	6.2	1.053	6.537	1.105
Cum. Distribution	2.235	0.470	2.061	0.427
Fundraise year	2012	14.720	2010	27.380
After entropy balancing	**Treat**		**Control**	
Variables	Mean	Variance	Mean	Variance
ln(Fund Age)	1.643	0.122	1.643	0.122
NAV	0.729	0.046	0.7291	0.046
ln(Fund size)	6.2	1.053	6.2	1.053
Cum. Distribution	2.235	0.470	2.235	0.470
Fundraise year	2012	14.720	2012	14.730

Panel B: High reputation GPs

Before entropy balancing	Treat		Control	
Variables	Mean	Variance	Mean	Variance
ln(Fund Age)	1.426	0.200	1.81	0.297
NAV	0.691	0.064	0.595	0.104
ln(Fund size)	7.778	1.468	8.016	1.339
Cum. Distribution	2.621	0.838	2.504	0.778
Fundraise year	2012	22.400	2010	25.320
After entropy balancing	**Treat**		**Control**	
Variables	Mean	Variance	Mean	Variance
ln(Fund Age)	1.426	0.200	1.426	0.200
NAV	0.6908	0.064	0.691	0.064
ln(Fund size)	7.778	1.468	7.778	1.468
Cum. Distribution	2.621	0.838	2.621	0.838
Fundraise year	2012	22.400	2012	22.400

Table IA8: **Additional tests using entropy-balanced sample**

This table reports regression results in Tables 6 (Panel A), and 8 (Panel B), but instead uses entropy-balanced samples. The table reports results for portfolio firms owned by low reputation GPs. See Table A1 for a complete list of variable definitions. Continuous variables are winsorized at the 1% level (valuation multiple variables are winsorized at 5%). *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Table 6

Dep var: Abn.	(1) Accruals	(2) Prod Cost	(3) Disc Exp
FundraiseFlag	0.000	0.019	0.156
	(0.03)	(0.54)	(1.05)
Controls	Y	Y	Y
Fund FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Pf Firm FE	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y
N	1,405	567	1,014
R-sq	0.959	0.978	0.977
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY

Panel B: Table 8

Dep var: Abn.	(1) Accruals	(2) Prod Cost	(3) Disc Exp
FundraiseFlag	0.014	0.129**	-0.269*
	(1.19)	(2.45)	(-1.95)
Controls	Y	Y	Y
Fund FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Pf Firm FE	Y	Y	Y
Pf Firm Country-Ind-Year FE	Y	Y	Y
N	2,370	862	1,637
R-sq	0.955	0.954	0.788
Clustering	Fund, Pf CIY	Fund, Pf CIY	Fund, Pf CIY