Private equity fund valuation management during fundraising

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Submitted to the Department of Management
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Management

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2022

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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 performance. The results are robust to a number of alternative explanations. Low reputation funds that employ some form of real 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 manipulating NAVs than timing fundraising periods.

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Acknowledgments

I thank my dissertation committee, Rodrigo Verdi (Chair), John Core, and Michelle Hanlon, for providing invaluable guidance for this paper. Without their help and guidance, I would not have been able to come this far. I especially thank my chair Rodrigo for taking the time and effort to guide me throughout the five years of my PhD journey. You have helped me grow not only as an academic researcher, but as a person.

I also thank all the accounting group faculty members at MIT. I thank Eric So for the invaluable help and training as the PhD program coordinator. I appreciate Nemit Shroff for his support and comments when presenting this idea as my second year summer paper and as my dissertation. I am grateful to Bala Dharan, Jacquelyn Gillette, S.P. Kothari, Andrew Sutherland, Joe Weber, and Chloe Xie for their helpful comments throughout multiple workshops.

I cannot forget the support from the fellow PhD students who studied before and after me. I am glad to have studied with Inna Abramova, Sam Anderson, Natalie Berfeld, Ki-soon Choi, Tim de Silva, Chuck Downing, Nick Guest, Zoe Han, David Kim, Jinhwan Kim, Suzie Noh, Heidi Packard, Georg Rickmann, Albert Shin, Gabriel Voelcker, Yuting Wang, Rachel Yoon, and Cindy Zhang. I am also glad and thankful for the opportunity to have Sam Anderson and Ki-soon Choi as my PhD cohort. I am grateful for their help and advice throughout the program. I wish the best of luck to you.

For this paper, I sincerely appreciate the helpful comments from Harvard Business School, London School of Economics, MIT, Singapore Management University, University of California, Berkeley, and University of Rochester. I thank Kael Kordonowy for excellent research assistance. I acknowledge the financial support from MIT Sloan School of Management.

I would like to thank my friends and family for the support and help throughout the PhD program. I am grateful to my parents, Ki Bok Baik and Yunhee Moon, my family-in-law, Kyung Hee Lee, Jung Ki Kim, and Ga-young Kim, for believing in me, praying for me, and helping me succeed. I thank my friends In Ha Hwang, Tony Lee, Jinho Lee, and Sunho (Sam) Shin for the support.

Finally, I am forever grateful and indebted to my wife Gi Eun Kim. Thank you for believing in me and for coming with me to Boston. Thank you for staying strong and for the emotional support whenever I was having a tough time, and thank you for enjoying with me during good times. Thank you for staying with me. I am sure a happy life is upon us and I will do my best for you to be happy.

Contents

List of Figures

List of Tables

1. Introduction

I study whether and how private equity (PE) fund investors (hereafter general partners or GPs) manipulate their fund performance during fundraising periods. The question is motivated by recent studies that (i) have found abnormally high private equity fund valuations during fundraising periods and (ii) that 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, 2021).[1] As I elaborate below, a fund's NAV can be decomposed into (i) valuation multiples (hereafter multiples or market multiples) and (ii) performance of the underlying investments. 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 is composed of valuation multiples and performance of the underlying investments. (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 private equity investments are private and do not have quoted market prices, GPs provide fair values using a number of valuation techniques. One the most common methods is to apply multiples

[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 whether private equity funds are timing their fundraising or manipulating fund valuations.

to their portfolio firm performance, 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 used the multiples method to value their investments. Throughout the paper, I assume that private equity funds report their NAVs using this method.

I predict that GPs use aggressive multiples, inflate portfolio firm performance, 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 private equity funds (e.g., Brown et al., 2019; Chung, Sensoy, Stern, and Weisbach, 2012). Second, GPs have the ability to inflate both multiples and portfolio firm performance. 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 performance 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 portfolio firm managers (Acharya, Kehoe, and Reyner, 2009).

Yet there are also reasons why funds 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. Second, GPs may use different methods than valuation multiples or earnings management to inflate their current fund performance. Finally, aggressive inflation of portfolio firm performance (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

[2] Indeed, prior studies demonstrate that the NAVs of private equity 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).

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, because many European countries require limited liability firms above a certain size threshold to disclose financial statement information. Furthermore, Europe is the second largest private equity 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[4] and 8,742 fund-quarter observations at the fund-level sample and 26,328 firm-year observations at the portfolio company-level sample.

Testing my main hypotheses requires two steps. First, I partition my 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 lack of reputation (and therefore validated skillsets) forces these funds to rely much more on their interim fund performance for fundraising. Second, using a design similar to a differences-in-differences design, I compare the valuation metric (either valuation multiple or firm performance) for funds with low (treated) and high (control) reputation.

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 metric used, instead of the aggregate NAV of the

[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, 2021), and because these funds invest in more mature firms. Therefore financial statement information is viewed to be more informative than venture capital fund investments. I follow Preqin's definition of buyout funds, following prior studies (e.g., Barber and Yasuda, 2017).

[4]For comparison, my sample is similar to the number of funds and fund-quarters reported by Barber and Yasuda (2017) (although they focus on US funds).

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 performance* abnormally increases during fundraising, I transition to portfolio firm data and test whether private equity investments owned by low versus high 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 earnings management, I use performance-matched accruals earnings management (AEM) and real earnings management (REM). I focus on measures of earnings management, instead of conventional measures of financial performance (e.g., ROA or sales growth) variables, because earnings management proxies provide clearer evidence of manipulation than do financial performance metrics. For the portfolio firm-level tests, I include portfolio-firm level control variables suggested by Dechow, Ge, and Schrand (2010) and variables used to obtain abnormal accruals in the first-step regression, as suggested by Chen, Hribar, and Melessa (2018) (see Section 6.2 for detailed explanation.). I additionally add portfolio firm fixed effects, portfolio firm country-year fixed effects, and portfolio firm industry-year fixed effects to capture time-invariant portfolio company characteristics and time-varying country and industry attributes, respectively.

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. The magnitude is slightly higher than results reported by Barber and Yasuda (2017) and Brown et al. (2019), who report a 9.1% increase in NAV percentile rank (ranked among same vintage peers) and approximately 5% point increase in changes in NAV.[5] 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.

[5]Note, however, the dependent variables used in these studies differ from mine.

Next, the results of the earnings management regression indicate that low reputation private equity portfolio firms engage in both AEM and REM (primarily by increasing abnormal production costs) to inflate their earnings. Specifically, low reputation buyout portfolio firms exhibit higher abnormal accruals (3.8% of portfolio firm assets), abnormal production costs (13.5% of portfolio firm assets),[6] which are consistent with my findings at the fund level. On the contrary, investments from high reputation GPs do not show (if anything, reduces EM) any evidence of earnings management during their fundraising.

To further rule out the timing hypothesis, for both tests, I propensity-score match each fundraising quarter with a nonfundraising quarter (and each fundraising portfolio firm-year with a nonfundraising portfolio firm-year) with a similar number of portfolio firms, fund age, fund NAV, fund reputation, and calendar year-quarter and re-estimate the main regressions. (See Figure IA2 for graphical depiction.) By matching with nonfundraising fund-quarters that have similar reputation, fund performance, and fund age,[7] I can mitigate the alternative hypothesis that GPs are timing their fundraising periods at their performance peak. For both tests, the main results are robust to the sample using propensity-score matching, which supports the argument that GPs manipulate fund performance, rather than time fundraising periods.

I address alternative explanations of my findings. One is that stronger abnormal earnings performance (proxied by earnings management) is merely a consequence of GPs' improvements of their investments' operational efficiency (e.g., Cohn, Mills, and Towery, 2014; Guo, Hotchkiss, and Song, 2011). To address this interpretation, I test the effects of private equity ownership during non-fundraising periods. To do so, I test whether private equity ownership is associated with earnings management by comparing portfolio firm-years with and without private equity ownership and find no significant relation with earnings management. Second,

[6]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.

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

I find that both valuation multiples and earnings management proxies reverse post fundraising, which reduces the concern that my results are capturing an increase in fund/portfolio firm efficiency, rather than capturing manipulations by the funds. By showing the reversals in multiples and in earnings management, I also verify that the findings are not attributable to reduced GP attention to their investments, a possibility raised by Brown et al. (2019).[8] 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 qualitatively unchanged. Fourth, I demonstrate that using random fundraising dates does not generate results consistent with the predicted signs. This rules out the possibility that my results may stem from measurement errors of fundraising dates. Last, I conduct a falsification test using a sample of venture capital transactions and buyout transactions with multiple investors and do not find any meaningful results, consistent with the argument that portfolio firms with multiple investors lowers the amount of influence made by one investor.

In my final set of tests, I examine the consequences of the overstated valuation multiples and financial performance of the underlying investments. While extant literature in general has found NAV management strategies to be unsuccessful, strategies executed at the portfolio firm level, especially real earnings management (which are thought to be harder to detect), could increase chances of low reputation funds to succeed in fundraising. I test and find that low reputation funds that use real earnings management (specifically abnormal production) is associated with successful fundraising (higher actual fundraise amount scaled by target fundraise size). However, the strategy is not effective for the investors of the current fund and does not increase the participation rate of current fund investors to the subsequent fund. This evidence is consistent with Hochberg, Ljungqvist, and Vissing-Jørgensen (2014) that

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

current fund investors have superior information and may not be fooled by GPs' efforts. Other strategies (managing valuation multiples or using accruals earnings management to increase their portfolio firms) are not associated with successful fundraising, consistent with prior literature.

This paper adds to the debate *whether* private equity funds 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 show that some forms of manipulation can 'fool' potential investors and increase the GPs' chances of successful fundraising, which is in contrast to previous findings. By doing so, this study extends the private equity 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, 2021; Jenkinson, Sousa, and Stucke, 2013).

My findings also contribute to the accounting literature on (i) the role of accounting information in Level III asset valuation accuracy and (ii) the reporting quality and earnings management of private firms. Regarding the role of accounting information, most of the research in this area has focused on whether accounting information and the financial performance of portfolio firms matters 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, 2020). 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 private equity industry, who are increasingly interested in this subject (Brown, Carman, and Giaimo, 2018).

With respect to the literature on financial reporting quality and earnings management, I contribute in three ways. First, by focusing on the effect of private equity investors on the earnings management of their portfolio firms, I demonstrate a case where long-term institutional shareholders induce earnings management by portfolio firms because of their short-term incentives during fundraising periods. Past studies (e.g., Bushee, 1998; Katz, 2009; Lisowsky and Minnis, 2020; Morsfield and Tan, 2006; Roychowdhury, 2006; Zang, 2012) find that, while short-term or transient investors induce earnings management, long-term investors suppress it. In this paper, I provide a case where long-term institutional owners can also prompt earnings management when these investors face short-term incentives.[9] Second, in a private equity fund setting, I show that 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 earnings management in private firms, which is an integral part of the economy and have different ownership structures.[10]

The paper is organized as follows. Section 2 provides institutional details on private equity fundraising. Section 3 writes literature review. Section 4 develops my hypotheses. Section 5 describes my data and sample selection process. Section 6 presents my research design. Section 7 discusses the main regression results. Section 8 discusses alternative explanations and falsification tests. Section 9 shows the consequences of performance management. Finally, Section 10- concludes.

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

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

2. Institutional background

2.1 The structure and the life-cycle of private equity funds

Private equity 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 private equity 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 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 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, 2019; 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). The abovementioned fund structure and timeline are standard globally.

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 subset of PE funds seem to have manipulated returns during fundraising. In a venture capital 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 Private equity fund valuation

How are private equity 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.[1] To value firms in the portfolios of funds (most of these firms 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 highest among all the listed valuation methods. For each portfolio firm a fund holds, the GP reports portfolio firm performance and its fair value.

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

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 private equity 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[2] 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 nonmutually exclusive ways for the GPs to manage their NAV valuation: (i) valuation multiples and (ii) portfolio firm performance.

Figure B1 provides an example of an actual private equity fund report.[3] 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 performance (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.

[2] The initiation year of a fund. See Table A1 for a detailed definition.

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

3. Literature review

For the GPs, fundraising is a critical event that can dictate their future, because the funds have finite lives and the GPs must raise new funds to continue their investing business (Gompers, 1996). Studies have shown that the GPs are motivated to overstate their fund performance because of the way in which PE funds are organized. For instance, Chung et al. (2012) theoretically model and empirically validate that interim performance (i.e., current fund NAVs) are more important for buyout funds than for venture capital funds, because the GPs can raise more funds if interim fund performance is better.

Given the significance of fundraising, recent studies postulate that there is a fund-level NAV manipulation (at least for a subset of funds) during fundraising periods. For instance, Jenkinson et al. (2013), using their sample of private equity funds invested by CalPERS, find that quarterly fund NAVs increase when the GPs are fundraising for their subsequent funds. Barber and Yasuda (2017) and Brown et al. (2019) use a broader sample of funds and find that the increased NAV occurs only in low reputation or under-performing funds. Brown et al. (2019) also contend that, although low reputation GPs seem to manipulate fund valuation, limited partners recognize this, and the GPs ultimately fail to raise subsequent funds. While studies find some forms of abnormal valuations during fundraising, each paper offers a different explanation. Notably, while Barber and Yasuda (2017) claim that the higher NAV is due to timing the fundraising periods when the fund's performance is at its peak, Brown et al. (2019) postulate that the increased performance is from NAV manipulation. Thus the literature is inconclusive on whether the increased NAVs are due to timing fundraising or manipulating the valuations.

I advance this debate by examining the components of the NAVs. Specifically, analyzing financial performance of individual portfolio firms and the valuation multiples applied to these investments can directly answer the question, because these two metrics relate directly to how private equity funds measure NAV. This paper's main distinction is that I can directly observe and analyze the components of the NAVs. This was impossible in previous studies because their authors mostly examine American funds investing in US firms and therefore lack financial statement information of the fund investments.

4. Hypothesis development

4.1 Do GPs inflate fund valuation multiples during fundraising?

I posit that GPs could use either inflated valuation multiples or their underlying investments' financial performance to manipulate their interim fund NAVs, for three reasons. First, theoretical models predict NAV inflation at least for a subset of GPs. For instance, Chung et al. (2012) analytically show that current fund performance for the GPs is important because they are indirectly compensated for their current performance by having the ability to raise larger subsequent funds (in addition to the direct compensation through profit sharing), which motivates the GPs to manipulate their current fund performance. More directly, Brown et al. (2019) theoretically model a costly signaling equilibria where low reputation GPs are forced to manipulate their fund returns, despite the limited partners seeing through these manipulations. Brown et al. (2019) empirically validate their predictions.

Second, manipulating valuation assumptions (i.e., multiples) is a plausible way to elevate the NAVs, because the GPs themselves calculate NAVs using their discretion. For instance, private equity valuation guidelines by IPEV (2018) suggest applying "a multiple that is appropriate and reasonable"; in other words, as long as the GPs can justify their multiples to their investors (and to regulators if audited), GPs can use aggressive multiples during fundraising. Indeed, Grant Thornton (2015) finds that approximately two-thirds of the survey respondents (who are GPs) internally calculate and report their investment valuations, despite the existence of third-party valuation service providers.

Conversely, there are reasons to believe why GPs might not inflate NAVs using valuation multiples. Excessive inflation can draw negative attention from both potential (and existing) investors and regulators. Limited partners, for their part, try to detect NAV overvaluation, by conducting due diligence or deriving their own version of existing fund valuation (Da Rin and Phalippou, 2017). NAV inflation has also been increasingly subject to regulators' attention. For instance, the European Union enacted Directive 2011/61/EU (also known as Alternative Investment Fund Managers Directive; hereafter AIFMD), which requires comprehensive disclosures on fund investments and risk exposure. In the United States, Brown et al. (2018) report that the Securities and Exchange Commission (SEC) has made this issue a top priority and audits marketing materials provided by some GPs, based on the Investment Advisers Act of 1940. Brown et al. (2018) recommend keeping close records of valuation/performance calculations because regulators often demand valuation records and assumptions when auditing fund performance. Inflated NAVs can be detected if there is scrutiny, which can severely constrain successful fundraising.

Another possibility is that, while GPs do manipulate NAVs, they could be manipulating using other methods. Although using valuation multiples is the most common valuation method private equity funds use, there are other ways of valuing portfolio firms. For example, Hüther (2021) mentions that some portfolio firms are valued at cost. GPs might thus manipulate NAVs by valuing investments at cost if they predict that investments have decreased in value (compared to the valuation the GPs paid at the time of investment). Similarly, valuation using cash flow models (such as DCF) is also prone to bias if the GPs use aggressive modeling assumptions (such as low discount rates or high future growth rates). If this is the case, valuation multiples are much less relevant predictors of the NAV increase.

Relatedly, reputational risks can also hinder the GPs from reporting aggressive NAVs. GPs raise new funds every three to five years (Metrick and Yasuda, 2010), and a loss of reputation can induce GPs to fail at fundraising for subsequent funds and ultimately go out of business.

To summarize, I hypothesize that funds would use valuation multiples as a way to inflate their current fund performance, since there are studies that show an increase in NAVs for a subset of GPs and since GPs can exert discretion in setting their valuation multiples.

Hypothesis 1. During fundraising, GPs inflate their current fund valuation by inflating their valuation multiples.

4.2 Do GPs inflate portfolio firm financial performance during fundraising?

GPs also can influence their underlying investments to take actions to increase their short-term financial performance, based on three investment characteristics of PE investments.[1] First, private equity funds invest majority equity stakes in investee firms and therefore have absolute control over their investments (Jensen, 1989). Second, GPs take board memberships at their portfolio firms for better monitoring and control (Cotter and Peck, 2001). In fact, Kaplan and Strömberg (2009) argue that the boards of portfolio companies in private equity funds are more active in governance than public company boards. In support of this claim, Acharya et al. (2009) find that private equity portfolio firm boards hold 12 board meetings a year and have more informal meetings, which is much more frequent than public firm board meetings. Third, GPs frequently replace existing management to align managerial interests with those of the GPs. For instance, Acharya et al. (2009) show that approximately 33% of CEOs or CFOs of the investee company are replaced within 100 days of a transaction's closing. Altogether, GPs have the ability to direct their investee firms to inflate their financial performance.

On the other hand, there are two reasons why GPs may not be able to direct their portfolio firms to inflate their financial performance. First, some studies show private equity

[1] Since I focus on buyout funds, I define "PE investments" as leveraged buyout transactions (LBO).

fund ownership is associated with less earnings management, which proxies for financial performance manipulation. Katz (2009) posits that private equity-backed firms have lower earnings management than comparable firms non-private equity-backed firms, and Hribar, Kravet, and Krupa (2021) find that earnings myopia is reduced post public-to-private private equity takeover. Second, manipulating portfolio firm financial performance can hurt firm fundamentals in the long run, depending on the method used. For instance, Cohen and Zarowin (2010) and Kothari, Mizik, and Roychowdhury (2016) find evidence of real earnings management during seasoned equity offerings and subsequent negative equity returns after the offerings as earnings management unwinds; Vorst (2016) also finds evidence that REM is associated with lower future operating performance. Therefore having portfolio firms manipulate their performance may reduce the exit price, and GPs may not choose to sacrifice their ultimate returns to achieve short-term goals (i.e., fundraising).

In sum, I predict that GPs would inflate portfolio firm financial performance as another way to increase their interim fund valuations, given the control the they have over their funds' underlying investments.

Hypothesis 2. During fundraising, GPs inflate their current fund valuation by inflating the financial performance of their portfolio firms.

5. 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 5.4 for a more detailed description), where many of the countries require both public and limited liability private firms under a certain size threshold to disclose their financial statements. Europe is also the second-largest private equity market in the world (McKinsey, 2021).

5.1 Data on private equity funds and their valuations

I use two datasets to create my sample. The first dataset is from Preqin, which offers detailed information on GPs, private equity 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.[1] In addition, Brown et al. (2015) show that US funds are well covered across all vintages, whereas non-US fund coverage dramatically improves from vintages in the

[1] 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 private equity 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.

1990s. I do not expect sample selection bias arising from this issue since my sample begins in 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 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 firm financial statements. 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.[2]

5.2 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,

[2]Note that I cannot observe unsuccessful fundraising attempts for funds without subsequent funds. Although this could raise a potential selection concern (i.e., my sample consists of successful funds and GPs), I argue that this would bias against my results because I expect unsuccessful funds to embellish their performance more aggressively than successful ones.

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.[3] The combined dataset has more than 162 million observations. For consistent currencies with Preqin, I convert all financial variables into US dollars, using exchange rates stored in Amadeus.

5.3 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 my anecdotal observation; that is, 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 done with the latest annual report (rather than using updated financials every quarter). In Table IA1, I re-estimate Equations 6.1 (Panel A) and 6.2 (Panel B) after keeping fourth-quarter fund reports and find qualitatively similar results.

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

[3]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.

any portfolio firm-year observations that were before the transaction date or after private equity 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 performance (i.e., EBITDA, sales, and total assets) and deflate them by fund size. Both portfolio firm performance and fund size are denoted in US dollars and should mitigate concerns arising from different currencies used in portfolio firms. The sample consists of 8,742 observations.

5.4 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, Netherlands, and Sweden. As discussed in Section 5, the high representation of US funds is likely because Preqin mainly collects data through FOIA requests to US pension funds. A potential concern related to this is that the sample funds may show selection bias in performance because those invested by US pension funds could be focused on high-performing GPs (regardless of reputation). While this issue could be valid, I argue that this will bias against my results because funds with lower skills/reputation GPs are expected to value their NAVs more aggressively during fundraising periods than would high reputation GPs.

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 United Kingdom and France are the largest private equity 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 1996 to 2018 (p1 and p99). The reported fund size and number are qualitatively similar to the statistics reported by Hüther (2021).

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 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.[4] 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 portfolio firms show more earnings management (three of four measures

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

statistically significant at least at the 5% level, as shown in Panel B), consistent with the results of Wongsunwai (2013), who find earnings management is stronger for investments backed by lower quality venture capital funds.

Accruals and production costs resemble the summary statistics reported by Zang (2012), but discretionary expenses are lower (for both samples). The difference may occur because I use the entire operating expenses as a proxy of discretionary expenses, rather than the sum of R&D and marketing expenses, as discussed above. Low reputation GP-owned portfolio firms are slightly larger in size (ln(Assets) mean value 17.636 versus 17.571), have lower leverage (Leverage 0.689 versus 0.835), are older (ln(Firm Age) 2.547 versus 2.425), are more profitable (ROA 0.035 versus -0.047), and have lower growth (Chg sales 0.070 versus 0.116).

6. Research design

6.1 Testing abnormal increases in fund valuation multiples

To test my first prediction, I partition my sample by GP reputation and estimate Equation 6.1. 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 reputation 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:[1] funds (i) that have raised less than three funds, (ii) that have raised less than \$1 billion in cumulative capital, and (iii) that do not have top quartile performing funds more than five years old as of fund inception. I adjust this definition of low reputation to funds that satisfy ((i) and (iii)) *or* ((ii) and (iii)). The reason for deviating from the

[1] 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.

approach of Barber and Yasuda is because low reputation GPs (with their definition) is 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 5.4 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).[2]

Using the partitioned sample, I estimate the following model:

$$\ln\left(\frac{NAV_{i,t}}{Performance_{i,t-1}}\right) = \beta_1 FundraiseFlag_{i,t} + \beta_2 FundControls_{i,t} + \alpha_j + \gamma_t \tag{6.1}$$

where $\ln\left(\frac{NAV_{i,t}}{Performance_{i,t-1}}\right)$ 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.[3] 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 do graphically show the reversals in multiples

[2]An alternative way to define low reputation is to modify Barber and Yasuda's definition to match their low/high reputation distribution. I do not define low reputation this way because there are multiple ways to match the distribution (since there are three criteria to construct low reputation).

[3]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., subsequent fund's first observed cash flow date) as fundraising closing date and find qualitatively similar results.

and earnings management 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 I show that multiples are higher during fundraising quarters, rather than showing lower multiples post fundraising.[4] In addition, setting high/low valuation multiples should be relatively less relevant to the attention GPs give to their investments. For funds that do not have subsequent funds, I define a fundraising quarter to be 13 to 28 quarters since inception, following Barber and Yasuda (2017). $Performance_{i,t-1}$ 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 private equity industry (IPEV, 2018). $FundControls_{i,t}$ denotes a battery of fund-level control variables I employ in the model and largely follows the literature on private equity fund reporting. The controls include natural log of the number of active portfolio firms in a given fund-quarter, natural log of fund age, and 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. 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, 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.[5] See Table A1 in the appendix for a complete list of variable definitions. I also include fund (α_j) and calendar year-quarter (γ_t) fixed effects for time-invariant GP and time attributes,

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

[5] 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 number of portfolio firms produces a similar effect.

respectively. Standard errors are clustered at the fund level.

One caveat in this approach is that the measure $Performance_{i,t-1}$ 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 a target firm, I expect the measurement error to be not too severe. Nevertheless, to cope with this issue, the variable $\ln\left(\frac{NAV_{i,t}}{Performance_{i,t-1}}\right)$ 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).[6]

6.2 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 earnings management to inflate their financial performance. I test for both accruals and real earnings management because GPs can influence their investments to employ not only aggressive accounting policies (AEM) but also conduct real actions (REM) to manipulate the financial performance of their investments.

Earnings management can largely come in two forms: accruals earnings management and

[6] 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).

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, such as providing excessive price discounts, drastic reductions in R&D expenses (or other discretionary expenses that may help the firm in the long term), and overproduction. GPs can force firms to engage in both methods, because buyout funds command absolute control over their investments through majority stake ownership, board memberships, and hiring management teams with aligned interests. Indeed, Gompers et al. (2016) show that GPs consider operational improvements to be one of the most important sources of added value to their portfolio firms.

Because controlling for firm performance is critical for my research design, I use performance-matched measures designed by Kothari, Leone, and Wasley (2005) across the EM variables I use. Specifically, I use three earnings management 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,[7] 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.[8]

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

$$EM_{i,t-1} = \beta_1 FundraiseFlag_{i,t} + \beta_2 PfFirmControls_{i,t-1} + \alpha_j + \gamma_t + \delta_i + \eta_{c,t-1} + \theta_{ind,t-1} \quad (6.2)$$

where $EM_{i,t-1}$ is one of the earnings proxies for portfolio firm i measured at year $t-1$;[9]

[7]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.

[8]Another measure of earnings management is abnormal discretionary sales, developed by Stubben (2010). I do not use this measure in my study because this proxy involves both accrual and real earnings management. However, in Figure 4 and Table IA5 I use this measure and find predicted results.

[9]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 6.1.

$FundraiseFlag_{i,t}$ equals one if a portfolio firm reporting date is classified as a fundraising period and zero otherwise; $PfFirmControls_{i,t-1}$ is a vector of portfolio firm-level control variables discussed by Dechow et al. (2010), and includes firm size (natural log of assets), leverage, profitability (ROA), sales growth, and firm age (natural log of firm age). α_j, and γ_t, denote fund fixed effects and calendar year-quarter fixed effects, respectively, and δ_i, $\eta_{c,t-1}$, and $\theta_{ind,t-1}$ denote portfolio firm fixed effects, portfolio firm country-year fixed effects, and portfolio firm industry-year (US SIC Code one-digit) fixed effects, respectively. Standard errors are clustered at the fund and portfolio firm (two-way) level.

6.3 Using earnings management variables as the dependent variable

One aspect that is important to discuss is that the earnings management variables are obtained through a two-step process. Earnings management 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) 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 private equity 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 6.2), 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 6.2. Chen et al. confirm that this approach generates unbiased coefficients and reliable t-statistics.

6.4 Propensity-score matching

6.4.1 Fund-level: Comparison against nonfundraising fund-quarters

The research design discussed so far cannot rule out the alternative explanation that the results may occur from GPs timing their fundraising periods. To address this concern, I propensity-score match fundraising quarters (treated fund-quarters) to nonfundraising quarters (control fund-quarters) that have similar fund and GP characteristics. By doing so, I restrict the control funds to have similar fundraising motives, timing, and reputation with the treated fund-quarters.

The matching at the fund level proceeds as follows. First, I conduct the following probit regression:

$$FundraiseFlag_{i,t} = \beta_1 \ln(\#PfFirms)_{i,t} + \beta_2 \ln(FundAge)_{i,t} + \beta_3 NAV_{i,t} + \varepsilon_{i,t} \tag{6.3}$$

where $\ln(\#PfFirms)_{i,t}$ is the natural log of the number of portfolio firms of fund i at quarter t, which controls for fund distribution and fund's stage; $\ln(FundAge)_{i,t}$ is the natural log of fund age, which controls for a fund's remaining life;[10] $NAV_{i,t}$ is the fund's valuation. This variable controls for the difference in valuations for fundraising and non-fundraising fund-quarters. See Table IA6 Panel A for the probit regression results. Using the probit regression results, for each treated fund-quarter, I propensity-score match (with 0.5 caliper) and keep one nearest neighbor fund-quarter as the control fund. I also require the control and treated funds to have the same reputation (low or high reputation) and be in the same calendar year-quarter. Taken together, the matching enables me to compare the treated fund-quarters to control fund-quarters that have similar fundraising motives (i.e., funds that have a similar remaining life of a fund, fund reputation, private equity fundraising market conditions) and therefore allows me to rule out the fundraising timing hypothesis. In Figure IA2, I graphically explain the matching procedure. While the full sample (top graph) is a list of fundraising/nonfundraising fund-quarters (described in years for brevity), the matched sample keeps one treated (fundraising) quarter with one control (nonfundraising) quarter from other funds that have similar characteristics described below. With the matched sample, I re-estimate Equation 6.1.

Table IA6 Panel B presents t-test results of the control variables after conducting propensity-score matching. The results are presented for the low-reputation GP sample. Across most variables (i.e., # of portfolio firms, GP age, fund age, fund size), I do not find statistically significant differences between treated and control groups; however, performance is still significantly different at the 10% level, and this requires the readers to interpret the results with caution.

[10]Since private equity funds, in general, have fixed lives of 10-12 years, fund age would be an important factor for a fund to be fundraising.

6.4.2 Portfolio firm-level: Comparison against nonfundraising fund-quarters

Similar to the fund-level propensity-score-matching research design, I conduct the following probit regression using the portfolio firm-level sample.

$$FundraiseFlag_{i,t} = \beta_1 \ln(\#PfFirms)_{i,t} + \beta_2 \ln(FundAge)_{i,t} + \beta_3 NAV_{i,t} + \varepsilon_{i,t} \qquad (6.4)$$

The equation is similar to Equation 6.3 but adds natural log of fund size, because fund size shows significant difference between treat and control funds in this sample if not controlled (while fund-level sample does not). Using the probit regression results (Table IA7 Panel A), I conduct PSM (with 0.5 caliper) and keep one nearest neighbor portfolio firm-year as control firms. Similar to the fund-level propensity-score matching, I require the treated and control observations to be in the same reported calendar year-quarter and have the same reputation. Table IA7 Panel B presents t-test results between treated and control firm-years; between control and treated firms, the means of most variables are statistically similar, with the exception of natural log of number of portfolio firms. In this sample, fund performance is well controlled for. Using this matched sample, I estimate Equation 6.2 but with fund, year-quarter, and portfolio firm country fixed effects to preserve variation within the portfolio firms.

7. Main results

7.1 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 Panel A presents the main test results of the first hypothesis. Columns (1) and (2) show results for funds with low reputation GPs, and columns (3) and (4) for those with high reputation GPs. Columns (1) and (3) ((2) and (4)) use EBITDA (sales) multiples as the dependent variable. Coefficients from columns (1) and (2) 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 4.74x (0.87x).

On the contrary, I find a negative coefficient (statistically significant for EBITDA multiples) for high reputation GP funds; fundraising is associated with a 11.9% decrease in EBITDA multiples, which translates to a drop of 4.64x. In the bottom row of the first two columns, I compare coefficients FundraiseFlag in columns (1) and (2) with those in columns (3) and (4), respectively. The χ^2 statistics of the differences between columns (1) and (3) ((2) and (4)) is 6.36 (5.69), respectively, which are both significant at the 5% level. Lower multiples of high reputation GP funds during fundraising are consistent with the findings of Brown et al. (2019), who show conservative NAVs with these funds during fundraising.

Panel B reports test results using the propensity-score-matched sample. The research design used in this panel should rule out the timing hypothesis by matching fundraising quarters to nonfundraising quarters with similar fundraising motives. (See Section 6.4.2 for details.) Again, columns (1) and (2) ((3) and (4)) show results for funds with low reputation GPs (high reputation GPs), and columns (1) and (3) ((2) and (4)) use ln(NAV/EBITDA) (ln(NAV/sales)) as dependent variables. Similar to Panel A, the coefficients are significant for tests using a sample of low reputation GPs. The coefficients are slightly larger than those of Panel A, showing 0.331 and 0.209 in columns (1) and (2), respectively. On the other hand, I do not find any statistically meaningful relation for funds with high reputation GPs. Overall, the results reported in this table support the argument that the increased multiples are from manipulation rather than timing fundraising periods.

7.2 Earnings management regression results

Figure 4 shows the levels of earnings management pre and post fundraising. Panels A, B, C, and D report mean values of abnormal accruals, abnormal discretionary sales, abnormal production costs, 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[1] and reversals of earnings management of portfolio firms before and after fundraising.

Table 5 Panel A presents the results of the regressions testing the second hypothesis. The first three columns 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 show the effects for firms under high reputation GPs. Consistent with the reputation results shown in Table 4, portfolio firms owned by low reputation GPs show strong signs of earnings management across two of the three regressions. In economic terms, portfolio firms during which their owner GPs are fundraising show 3.8% 13.5% increase and 12.6% decrease in abnormal accruals, production costs, and discretionary expenses respectively, consistent with my predictions. Considering the normal accruals of my sample is -0.018 and the changes in accounts receivables is 0.028, the effect is economically significant. Furthermore, the coefficient for abnormal production costs is high, compared to previous literature (e.g., Gunny (2010) and Roychowdhury (2006) report coefficients of approximately 5%); one possible explanation is that my sample consists of private firms, which are typically smaller than the US public firms used in both studies, and smaller size could cause a larger coefficient. On the other hand, I do not find a statistically significant result using abnormal discretionary expenses, although the sign of the coefficient is consistent with the prediction. The economic magnitude is in line with the coefficients reported in previous studies. In contrast, across all specifications, I do not find any statistically meaningful results for firms owned by high reputation GPs. Similar to the fund-level tests, the differences in coefficients of FundraiseFlag between low reputation and high reputation portfolio firm sample are significant at the 5% level for abnormal accruals. The coefficients for abnormal production costs are marginally different (statistical significance 0.128). 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

[1] I observe lower abnormal discretionary expenses during fundraising, considered to be indicative of earnings management.

GPs are using earnings management to inflate portfolio firm performance.

Panel B reports the results using the propensity-score-matched sample. Columns (1)-(3) (columns (4)-(6)) report coefficients using low reputation GP (high reputation GP) owned portfolio firms. I observe regression coefficients consistent with Panel A. In fact, the coefficients are statistically stronger using this sample. In contrast, high reputation GP-owned portfolio firms show a substantial decrease in abnormal accruals, consistent with prior studies that show conservative valuations during fundraising among high reputation GPs (e.g., Wongsunwai, 2013).

8. Alternative explanations and falsification tests

8.1 Effects of private equity ownership

The first alternative interpretation of my results discussed in Section 7.2 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 private equity ownership. Therefore I test whether earnings management proxies significantly change PE ownership. Specifically, I estimate the following regression:

$$EM_{i,t-1} = \beta_1 PEOwn_{i,t-1} + \beta_2 PfFirmControls_{i,t-1} + +\alpha_j + \gamma_t + \delta_i + \eta_{c,t-1} + \theta_{ind,t-1} \quad (8.1)$$

where the variable of interest $PEOwn_{i,t-1}$ 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 private equity ownership) to clearly show the effects of PE ownership without fundraising motives.

Table 6 demonstrates the regression coefficients. Columns (1)-(3) show results for low reputation GP-owned portfolio firms, and columns (4)-(6) for high reputation GP-owned 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 private equity ownership. Furthermore, results in columns (4)-(6) (high reputation GP portfolio firms) demonstrate a *decrease* in abnormal accruals and an *increase* in abnormal discretionary expenses (which suggests lower earnings management), which does not support the alternative interpretation.

8.2 Reversals post fundraising

The second concern is that the abnormal surge in multiples and earnings management 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). To address this argument, I graphically present valuation multiples pre and post fundraising in Figure 3 (also discussed in Section 7.1). 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 decrease 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 private equity industry (Grant Thornton, 2015).

In a similar vein, Figure 4 presents mean values of earnings management variables pre and post fundraising. Panel A, B, C, and D show mean values for abnormal accruals, abnormal discretionary sales, 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 earnings management, a result consistent with the findings in Figure 3.

In sum, the evidence suggests a sharp reversal post fundraising for both multiples and earnings management, which is counter to the argument that the increase during fundraising is an efficient outcome.

8.3 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, earnings management 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 earnings management before IPOs. To alleviate the concern, in Table 7, I drop portfolio firm-years with less than two years before their exit dates and re-estimate Equation 6.2 for low reputation GP-owned portfolio firms. The results remain qualitatively similar to the results shown in Table 5.

8.4 Random fundraising dates

To test against the argument that my results are robust to random measurement errors in fundraising dates, I create random fundraising dates and re-estimate regressions for both fund-level and portfolio firm-level tests (i.e., Equation 6.1 and 6.2). Specifically, I assign random fundraising dates that match the distribution with the samples I used in my main tests (i.e., 0.108 of fund-level sample, 0.107 of firm-level sample).

Table 8 shows the results. Panel A (Panel B) reports results for fund-level (portfolio firm-level) tests. Throughout all columns, I do not find any statistically meaningful relationship using random fundraising dates as independent variables of interest. To additionally ensure robustness, I repeat the above procedure 100 times and report how many incidents show coefficients statistically significant in the predicted sign. For 100 fund-level tests, less than five iterations show significant coefficients in the predicted direction (three times using ln(NAV/EBITDA) as the dependent variable; four times using ln(NAV/sales) as dependent variable). I also find that less than 10 iterations (out of 100) show significant coefficients in the predicted direction. Specifically, regressions using abnormal accruals, discretionary sales, production costs, and discretionary expenses as dependent variables have two, six, nine, and four iterations that have significant coefficients in the predicted direction, respectively. Overall, the findings suggest that my results are not driven by fundraising date measurement errors.

8.5 Falsification tests using portfolio firms with multiple investors

To further triangulate my main results, I exploit the amount of influence an investor can make to their portfolio firms. More specifically, I explore whether portfolio firms invested by multiple investors show similar behavior when one of the investors are raising subsequent funds. I anticipate that, one investor would have much lesser influence to their portfolio firms if multiple investors are invested in a portfolio firm. To test this idea, I pool *venture capital* and buyout investments that have multiple institutions as shareholders (i.e., 'club deals') and test whether these firms manage earnings when one of the GPs are raising funds, by re-estimating Equation 6.2. I present the results in Table 9; 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 tits portfolio firm if other shareholders are involved.

9. 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 investors, it is possible that GPs that use certain strategies may be able to fool the investors. For instance, one conjecture could be that, managing NAVs through valuation multiples could have a much higher chance of detection than through manipulating individual portfolio firm's financial performance.

Broadly, there could be two types of consequences from managing current fund performance: (i) fundraising success and (ii) current fund investor retention. Retaining current fund investors is also an important aspect of fundraising for the GPs they possess a significant amount of hold-up information which affects other investors' fund investment decisions (Hochberg et al., 2014). Furthermore, current fund investors may have better information about the investments in the current fund, and may be less likely to 'become fooled' by embellished performance. I test these consequences in this section.

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 earnings management) of a fundraising period for each fund. There is one observation per fund. Then, I measure two fundraising outcome variables, which are (i) the actual fundraise amount raised divided by targeted fundraise amount and (ii) the number of existing fund investors divided by the number of subsequent fund investors, both obtained from Preqin. The first proxy measures the fundraising success, and the second proxy measures the willingness of current fund investors to invest in the subsequent fund. Next, I estimate the following regression:

$$
\begin{aligned}
Outcome_{i+1} = {} & \beta_1 MeanMultiple_i(MeanEM_i) \times LoPE_i + \beta_2 MeanMultiple_i(MeanEM_i) \\
& + \beta_3 LoPE_i + \beta_2 Controls_i + \alpha_c + \eta_v + \gamma_y
\end{aligned}
\tag{9.1}
$$

where $Outcome_{i+1}$ is one of the two fundraising outcome variables explained above for the subsequent fund, i.e., $Actual/Target$ and $CurrentInv/NextInv$; $MeanMultiple_i$ and $MeanEM_i$ are the mean of valuation multiples (i.e., ln(NAV/EBITDA) or ln(NAV/Sales)) and the mean of earnings management proxies, respectively; $LoPE_i$ equals one if the fund is a low reputation PE fund and zero otherwise; $Controls_i$ include fund-related characteristics, and include natural log of fund size, mean of natural log of number of portfolio firms, mean of natural log of fund age, mean of natural log of GP age; α_c, η_v, γ_y denote GP country, vintage, and fundraise year fixed effects, respectively. Here, I pool low and high reputation funds instead of separating them like our main tables because doing so severely reduces the power of my test.

Table 10 presents the results. Panel A (Panel B) shows results using valuation multiples (earnings management). In Panel A, columns (1) and (2) ((3) and (4)) use $Actual/Target$ ($CurrentInv/NextInv$) as the dependent variable. My coefficient of interest, $Multiple \times LoPE$ is statistically insignificant across all specifications, suggesting that higher multiples do not contribute to fundraising success. Both external investors and current fund investors are able to unravel the managed multiples. This is consistent with prior literature that shows the investors look through manipulated current fund performance.

In Panel B, columns (1), (2), and (3) use $Actual/Target$ and columns (4), (5), and (6) use $CurrentInv/NextInv$ as the dependent variable, respectively. In column (2), when abnormal production cost is interacted with low reputation PE variable, I find a positive and significant coefficient. The evidence suggests that manipulating earnings through abnormal production cost is somewhat effective to increasing the chances of low reputation GPs raising funds successfully. Meanwhile, the variable $LoPE$ is negatively significant, implying that low reputation funds, without earnings management, has lower chances of raising funds than high reputaton ones. However, column (5) suggests that this strategy is not effective enticing existing fund investors, possibly because they have better information about the current funds' investments.

10. Conclusion

In this paper, I investigate whether and how private equity 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 performance through accrual and real earnings management. The results are consistent with the manipulation hypothesis more than the fundraising timing hypothesis. My results are robust to a battery of alternative explanations. The results also suggest that low reputation funds conducting real earnings management are somewhat successful in raising subsequent funds.

My paper contributes to the academic literature in three ways. First, it contributes to the private equity literature by showing the mechanisms behind NAV inflations of private equity funds during fundraising periods. My findings suggest that low reputation GPs manipulate fund returns via valuation multiples at the fund level and earnings management at their portfolio companies. Second, I contribute to the literature that studies the relationship between accounting information and the reporting of private equity fund valuations, 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 the earnings management and financial reporting quality literature by showing private firms under long-term institutional investors can manage earnings when the investors face myopic motives, by showing that valuation multiples could be manipulated in private equity fund settings, and by enhancing the understanding of earnings management in private firm settings.

Appendices

A. Variable definitions

Table A1: **Variable definitions**

Variable name	**Definition**
Variables used in tests	
Abn. Accruals	Abnormal accruals which measures accruals earnings management. See Appendix C for detailed derivations.
Abn. Disc Exp	Abnormal discretionary expenses (operating expenses in my setting), and measures excessive cost cuts. See Appendix C for detailed derivations.
Abn. Prod Cost	Abnormal production costs, and measures abnormal production. See Appendix C for detailed derivations.
Abn. Disc Sales	Abnormal discretionary sales from Stubben (2010). See Appendix C for detailed derivations.
Actual/Target	Actual fund raised divided by fundraise target size. Fundraise target is set by the GPs themselves.
Chg Sales	Changes in sales, scaled by lagged total assets.
CurrentInv/NextInv	Number of current fund investors that invested in the subsequent fund, divided by number of total number of subsequent fund investors.
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.
Leverage	Leverage of portfolio firm-year.
ln(Assets)	Natural log of portfolio firm total assets, measured in local currency.

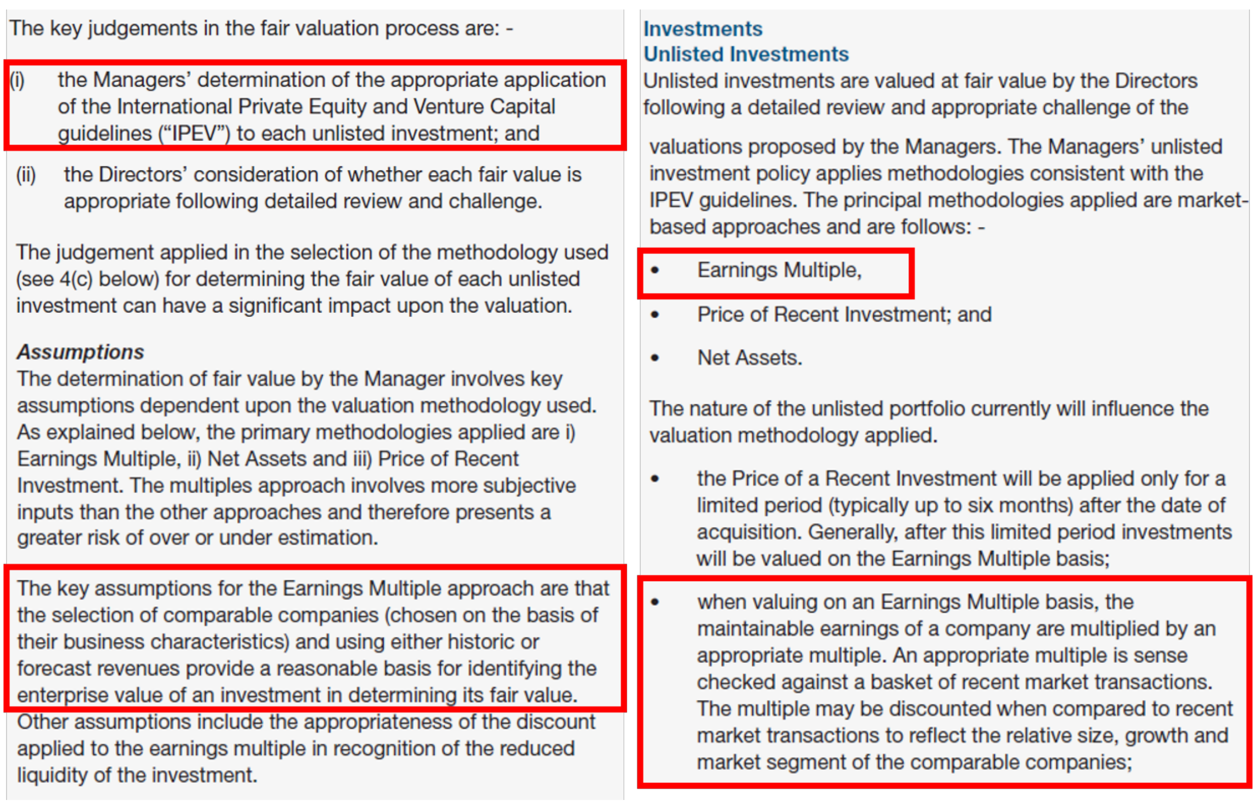
Table A1 – continued from previous page

Variable name	Definition
ln(Firm Age)	Natural log of portfolio firm age.
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.
LoPE	Equals one if the reputation of a PE fund is low, and zero otherwise.
MeanEM	Mean of one of three main earnings management proxies (abnormal accruals, abnormal production costs, abnormal discretionary expenses) for each fund during fundraising periods.
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 certain 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.

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%

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,[1] and that the GPs find "revenue/demand increases" as the most important value-add which the GPs contribute to the portfolio firms.[2]

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 et al. (2016) find that, markets fail to detect earnings management only when it is backed by REM; Cohen and Zarowin (2010); 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

[1] 97.1% of the respondents answered operational improvements as an important driver of returns.

[2] 70.3% of the respondents responded that GPs can add value to portfolio firms by increasing revenue or by improving demand.

and Collins (2002)) to obtain total accruals because cash flow statement data in Amadeus is extremely scarce. Hence, I recommend the readers to interpret my results with caution.

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.

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.[3] 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 Discretionary sales

As an alternative to discretionary accruals, I also use abnormal sales from Stubben (2010) in Table IA5. An advantage of using this measure is that one can directly and intuitively observe the abnormal increases in *revenues*, which is the most important and common way of managing earnings. To measure discretionary sales, I use the discretionary sales model from Stubben (2010), by estimating the following model for each country, industry, and year:

$$\frac{\Delta AccRec_{i,t}}{A_{i,t-1}} = \beta_1 \frac{\Delta S_{i,t}}{A_{i,t-1}} + \gamma_{i,t} \tag{C.4}$$

where $\frac{\Delta AccRec_{i,t}}{A_{i,t-1}}$ is the changes in accounts receivable, scaled by lagged total assets, and $\frac{\Delta S_{i,t}}{A_{i,t-1}}$ is the changes in sales, scaled by lagged total assets. The $\gamma_{i,t}$ is the abnormal sales variable.

[3] 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.

C.4 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).

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

	(1) Accruals	(2) Disc. Sales	(3) Prod Cost	(4) 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	0.069	-0.427	
	(0.74)	(0.65)	(-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	0.030	0.175	133.630***
	(0.15)	(0.96)	(1.04)	(694.15)
Mean N	1,242	1,670	467	603
Mean Adj. R-sq	0.277	0.189	0.819	0.380
# of groups		56,524		

C.5 Performance-matching

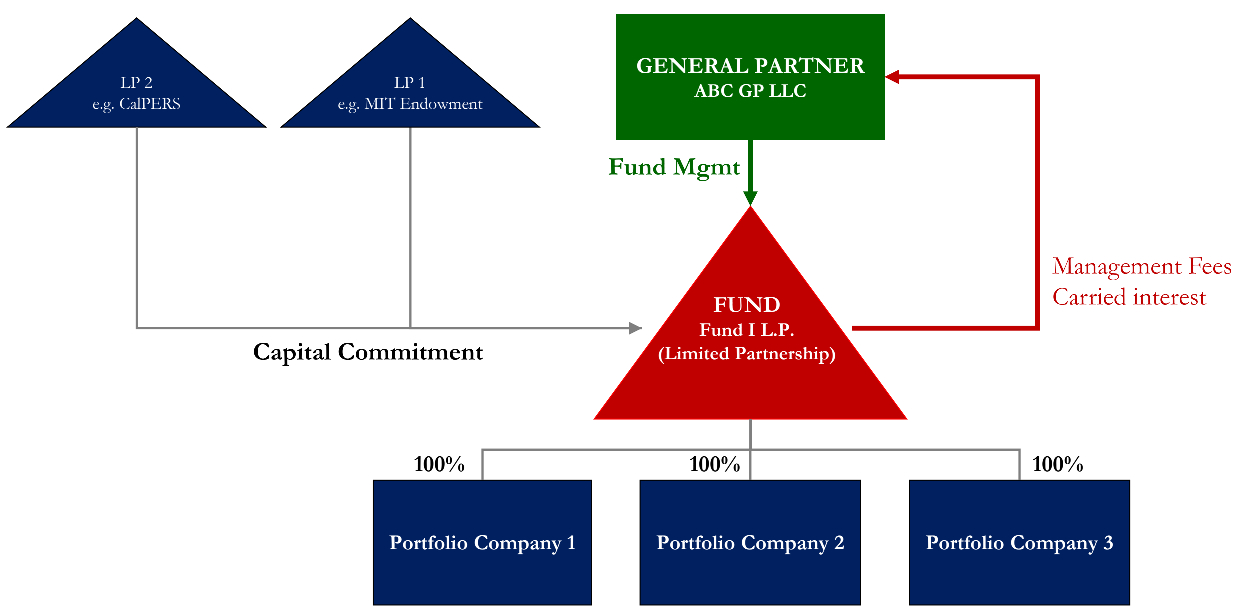
Across all variables, I conduct performance-matching using two steps, following Kothari et al. (2005). First, for each firm-year i, t, I identify another firm-year j, t within the same country-industry (SIC two-digit) that has closest ROA with firm-year i, t. Then, I subtract EM of firm-year j, t from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

D. Figures

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.

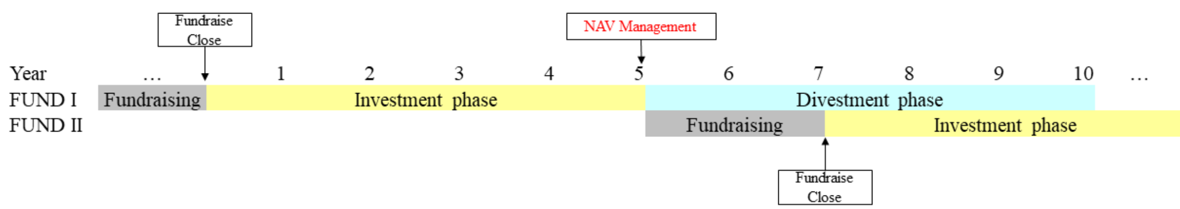


Figure 2: **Valuation numerical example**

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.

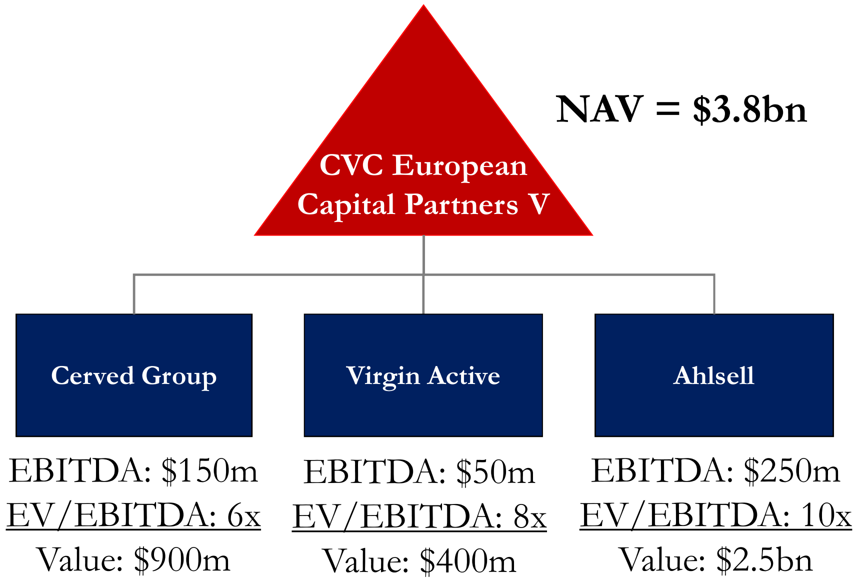
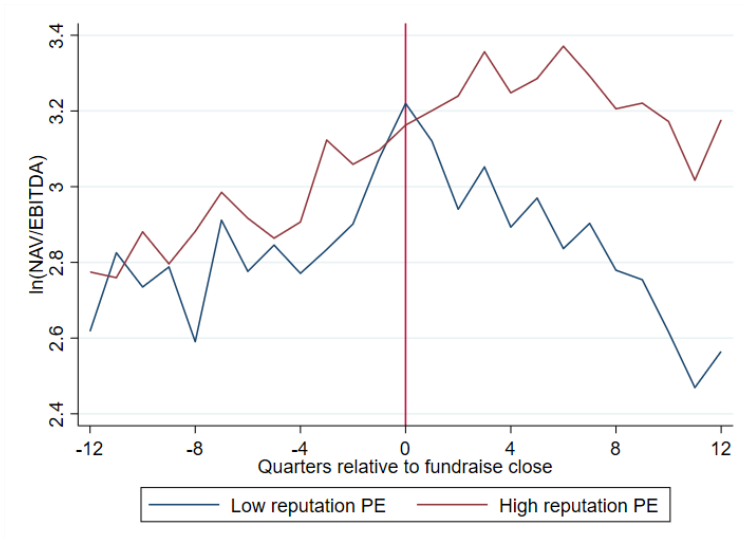


Figure 3: **Valuation multiples pre-post fundraising**

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 funds.

Panel A: EBITDA multiple



Panel B: Sales multiple

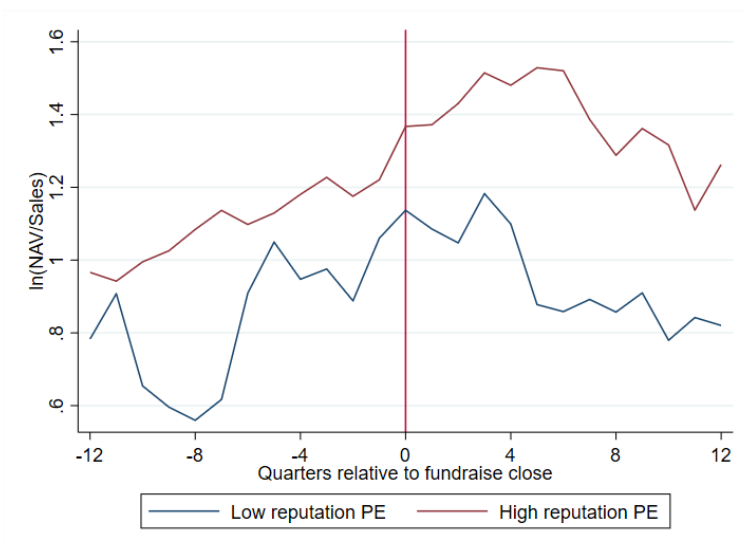
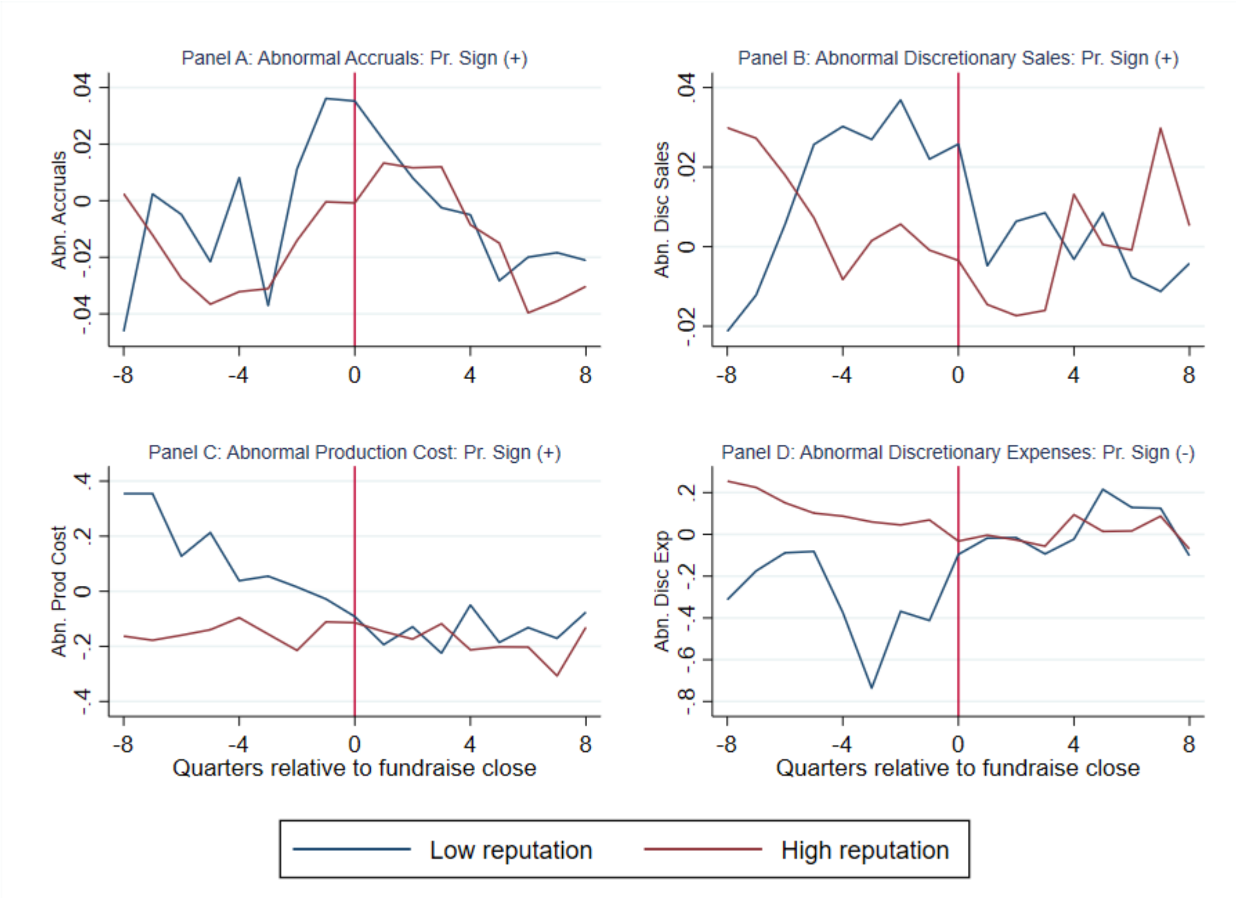


Figure 4: **Earnings management pre-post fundraising**

This figure plots mean values of abnormal accruals (Panel A) and abnormal discretionary sales (Panel B) abnormal production costs (Panel C), and abnormal discretionary expenses (Panel D) 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 funds.



E. Tables

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	Variables	N	Mean	Std	p1	Median	p99
All funds	Fund size	410	2,903.772	3,694.071	65.87	1431.975	18000
	Fund #	410	5.420	2.887	1	5	10
	Vintage	410	2,009.276	5.293	1998	2009	2018
Low reputation	Fund size	102	897.390	1,071.508	47.37	471.395	3600
	Fund #	102	2.559	1.480	1	2	8
	Vintage	102	2,007.529	5.464	1996	2007	2017
High reputation	Fund size	308	3,568.224	4,002.740	138.9	2060.85	18380
	Fund #	308	6.367	2.600	3	6	10
	Vintage	308	2,009.854	5.114	1998	2011	2018

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. All 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

Variables	N	Mean	Std	p1	Median	p99
FundraiseFlag	8,709	0.112	0.316	0	0	1.000
NAV/Sales	8,709	9.488	15.011	0.088	2.213	47.720
NAV/EBITDA	8,699	35.576	56.939	(35.605)	12.441	161.677
ln(NAV/Sales)	8,709	0.879	1.815	(2.434)	0.794	3.865
ln(NAV/EBITDA)	7,800	2.685	1.766	(2.612)	2.755	5.086
ln(# of Portfolio firms)	8,709	1.652	0.759	0.693	1.609	3.497
ln(Fund Age)	8,709	1.742	0.624	0	1.792	2.773
ln(GP Age)	8,709	3.036	0.665	0	3.178	4.431

Panel B: Mean values by fund's GP reputation

	High reputation		Low reputation		
Variables	N	Mean (1)	N	Mean (2)	(1) - (2)
FundraiseFlag	6,392	0.116	2,317	0.101	0.016**
NAV/Sales	6,392	10.55	2,317	6.557	3.993***
NAV/EBITDA	6,382	38.986	2,317	26.182	12.804***
ln(NAV/Sales)	6,392	1.001	2,317	0.545	0.456***
ln(NAV/EBITDA)	5,782	2.783	2,018	2.406	0.377***
ln(# of Portfolio firms)	6,392	1.72	2,317	1.465	0.256***
ln(Fund Age)	6,392	1.699	2,317	1.86	-0.162***
ln(GP Age)	6,392	3.157	2,317	2.703	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	Std	p1	Median	p99
Abn. Accruals	18,362	(0.008)	0.275	(0.910)	0	0.831
Abn. Prod Cost	5,545	(0.120)	0.849	(2.773)	0	2.375
Abn. Disc Exp	9,683	0.064	1.241	(3.793)	0	3.582
FundraiseFlag	26,328	0.119	0.324	0	0	1.000
ln(Total Assets)	26,328	17.847	2.414	11.850	17.860	22.846
Leverage	26,328	0.727	0.605	0.020	0.689	2.488
ln(Firm Age)	26,328	2.505	0.833	0.693	2.565	4.277
ROA	26,328	0.041	0.232	(0.625)	0.040	0.577
Chg Sales	26,328	0.097	0.461	(1.921)	0.042	1.986

Panel B: Mean values by fund's GP reputation

	High reputation		Low reputation		
Variables	N	Mean (1)	N	Mean (2)	(1) - (2)
Abn. Accruals	14,710	-0.01	3,652	0.001	-0.012**
Abn. Production Cost	4,278	-0.145	1,267	-0.035	-0.110***
Abn. Disc Expense	7,420	0.108	2,263	-0.08	0.188***
FundraiseFlag	21,448	0.121	4,880	0.11	0.011**
ln(Total Assets)	21,448	17.895	4,880	17.636	0.260***
Leverage	21,448	0.736	4,880	0.689	0.047***
ln(Firm Age)	21,448	2.496	4,880	2.547	-0.051***
ROA	21,448	0.042	4,880	0.035	0.008**
Chg Sales	21,448	0.103	4,880	0.07	0.032***

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

Panel A presents estimates of the following regression:

$$\ln\left(\frac{NAV_{i,t}}{Performance_{i,t-1}}\right) = \beta_1 FundraiseFlag_{i,t} + \beta_2 Fundcontrols_{i,t} + \alpha_j + \gamma_t$$

Panel B presents regression results using equation similar to Panel A but uses PSM-matched sample with treated-control pair fixed effects instead of fund fixed effects. See Table A1 for a complete list of variable definitions. Dependent variables are winsorized at the 5% level, following Barber and Yasuda (2017); all other continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: All sample

	Low reputation		High reputation	
	(1)	(2)	(3)	(4)
Dependent variable:	ln(NAV/EBITDA)	ln(NAV/Sales)	ln(NAV/EBITDA)	ln(NAV/Sales)
FundraiseFlag	0.182*	0.227**	-0.119*	-0.070
	(1.78)	(1.98)	(-1.83)	(-1.30)
ln(# of Portfolio firms)	-0.812***	-0.991***	-0.530***	-0.831***
	(-4.35)	(-4.70)	(-3.90)	(-7.04)
ln(Fund age)	1.653***	1.379***	2.473***	2.238***
	(4.35)	(3.52)	(9.59)	(11.96)
ln(GP age)	1.492*	0.643	-0.693**	-0.397*
	(1.98)	(0.68)	(-2.01)	(-1.90)
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	0.766	0.813
Clustering	Fund	Fund	Fund	Fund
SUR χ^2 test vs. hi-rep funds	6.36**	5.69**		
Prob > χ^2	0.012	0.017		

Panel B: PSM-matched sample

	Low reputation		High reputation	
	(1)	(2)	(3)	(4)
Dependent variable:	ln(NAV/EBITDA)	ln(NAV/Sales)	ln(NAV/EBITDA)	ln(NAV/Sales)
FundraiseFlag	0.331**	0.209*	-0.021	0.015
	(2.11)	(1.73)	(-0.26)	(0.25)
Controls	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
N	356	356	1,335	1,335
R-sq	0.900	0.936	0.864	0.912
Cluster	Fund	Fund	Fund	Fund

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

Panel A presents estimates of the following regression:

$$EM_{i,t-1} = \beta_1 FundraiseFlag_{i,t} + \beta_2 PfControls_{i,t-1} + \alpha_j + \gamma_t + \delta_i + \eta_{c,t-1} + \theta_{ind,t-1}$$

where coefficient β_1 is the coefficient of interest. The table partitions the sample by fund's GP reputation; columns (1)-(3) (columns (4)-(6)) report results for portfolio firms owned by low (high) reputation GPs. Panel B presents similar equation to Panel A but instead uses PSM-matched sample with fund, year-quarter, and portfolio firm country fixed effects. See Table A1 for a complete list of variable definitions. All continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Main sample

	Low reputation			High reputation		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
FundraiseFlag	0.038**	0.135	-0.126	-0.010	-0.022	-0.061
	(2.24)	(1.50)	(-1.01)	(-0.84)	(-0.35)	(-0.98)
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
Pf firm Ind-Year FE	Y	Y	Y	Y	Y	Y
N	3,652	1,267	2,263	14,710	4,278	7,420
R-sq	0.723	0.840	0.639	0.488	0.564	0.520
Clustering	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm
SUR χ^2 test vs. hi-rep funds	5.25**	2.31	0.24			
Prob > χ^2	0.022	0.128	0.626			

Panel B: PSM-matched sample

	Low reputation			High reputation		
	(1)	(2)	(3)	(4)	(5)	(6)
Depdendent var: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
FundraiseFlag	0.068*	0.717**	-0.356	-0.052***	-0.081	0.128
	(1.80)	(2.14)	(-1.57)	(-2.74)	(-0.84)	(1.11)
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 Country FE	Y	Y	Y	Y	Y	Y
N	658	202	375	3,253	946	1,618
R-sq	0.489	0.741	0.520	0.401	0.587	0.484
Clustering	Fund	Fund	Fund	Fund	Fund	Fund

Table 6: **Effects of PE ownership**

This table presents estimates of the following regression:

$$EM_{i,t-1} = \beta_1 PEOwn_{i,t-1} + \beta_2 PfControls_{i,t-1} + \alpha_j + \gamma_t + \delta_i + \eta_{c,t-1} + \theta_{ind,t-1}$$

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-owned portfolio firms. See Table A1 for a complete list of variable definitions. All 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 variable: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
PEOwn	-0.004	-0.056	0.124	-0.021**	0.036	-0.084
	(-0.24)	(-0.71)	(1.26)	(-2.32)	(0.55)	(-1.62)
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
Pf Firm Ind-Year FE	Y	Y	Y	Y	Y	Y
N	6,141	3,665	2,145	31,777	16,451	9,138
R-sq	0.485	0.512	0.347	0.374	0.423	0.455
Clustering	Fund, Pf firm	Fund, Pf firm	Fund, Pf firm	Fund, Pf firm	Fund, Pf firm	Fund, Pf firm

Table 7: **Removing firm-years close to exit**

This table presents estimates of the following regression, after removing portfolio firm-years less than two calendar years apart from the exit year:

$$EM_{i,t-1} = \beta_1 FundraiseFlag_{i,t} + \beta_2 PfControls_{i,t-1} + \alpha_j + \gamma_t + \delta_i + \eta_{c,t-1} + \theta_{ind,t-1}$$

where coefficient β_1 is the coefficient of interest. The table shows results only for low reputation GP-owned portfolio firms. See Table A1 for a complete list of variable definitions. All 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	0.032*	0.145	-0.136
	(1.88)	(1.62)	(-1.06)
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
Pf firm Ind-Year FE	Y	Y	Y
N	3,569	1,230	2,198
R-sq	0.731	0.852	0.649
Clustering	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm

Table 8: **Random fundraise dates**

This table re-estimates Equation 6.1 (Panel A) and Equation 6.2 (Panel B) using randomly generated fundraise flag dates (variable $FundraiseFlag\_Rand$). Samples using low reputation fund GPs and their portfolio firms are reported. 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. All continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund level

Low reputation GPs Dependent variable:	(1) ln(NAV/EBITDA)	(2) ln(NAV/Sales)
FundraiseFlag_Rand	-0.041	-0.023
	(-0.60)	(-0.40)
<10% sig with pr. Sign	1/100	7/100
Fund FE	Y	Y
Year-Quarter FE	Y	Y
N	2,018	2,317
R-sq	0.791	0.759
Cluster	Fund	Fund

Panel B: Portfolio-firm level

Dependent variable: Abn.	(1) Accruals	(2) Prod Cost	(3) Disc Exp
FundraiseFlag_Rand	-0.009	-0.004	-0.036
	(-0.99)	(-0.11)	(-0.51)
<10% sig with pr. sign	9/100	7/100	3/100
Controls	Y	Y	Y
Fund FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
Pf Firm FE	Y	Y	Y
Pf Firm Country-Year FE	Y	Y	Y
Pf Firm Ind-Year FE	Y	Y	Y
N	3,652	1,267	2,263
R-sq	0.722	0.839	0.638
Clustering	Fund, Pf firm	Fund, Pf firm	Fund, Pf firm

Table 9: **Falsification test using VC and multiple investors**

This table shows the results estimating Equation 6.2 using a sample of venture capital transactions and buyout transactions with multiple investors. See Table A1 for a complete list of variable definitions. All continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Depdendent variable: Abn.	(1) Accruals	(2) Prod Costs	(3) Disc Exp
FundraiseFlag	-0.053	-0.067	-0.145
	(-1.07)	(-0.92)	(-0.75)
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	2,915	930	1,764
R-sq	0.723	0.851	0.756
Clustering	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm

Table 10: **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:

$$\begin{aligned} Outcome_{i+1} = &\ \beta_1 MeanMultiple_i(MeanEM_i) \times LoPE_i + \beta_2 MeanMultiple_i \\ &+ \beta_3 LoPE_i + \beta_4 Controls_i \alpha_c + \eta_v + \gamma_y \end{aligned}$$

See Table A1 for complete list of variable definitions. All continuous variables are winsorized at the 1% level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund-level sample

	(1)	(2)	(3)	(4)
Dependent variable:	ActualRaised/Target	ActualRaised/Target	CurrentInv/NextInv	CurrentInv/NextInv
ln(NAV/EBITDA) × LoPE	0.027		0.002	
	(0.88)		(0.04)	
ln(NAV/Sales) × LoPE		-0.009		-0.022
		(-0.37)		(-0.70)
ln(NAV/EBITDA)	-0.022		0.010	
	(-1.33)		(0.41)	
ln(NAV/Sales)		-0.016		0.012
		(-0.87)		(0.49)
LoPE	-0.144	-0.055	-0.045	-0.005
	(-1.45)	(-1.09)	(-0.30)	(-0.07)
GP Country FE	Y	Y	Y	Y
Vintage FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
N	225	248	195	215
R-sq	0.276	0.293	0.060	0.296
Cluster	Fund	Fund	Fund	Fund

Panel B: Portfolio firm-level

Dependent variable:	(1) Actual/Target	(2) Actual/Target	(3) Actual/Target	(4) CurrentInv/NextInv	(5) CurrentInv/NextInv	(6) CurrentInv/NextInv
Abn. Accruals × LoPE	-0.306			-0.334		
	(-1.09)			(-0.80)		
Abn. Prod Cost × LoPE		0.351*			0.112	
		(1.71)			(0.42)	
Abn. Disc Exp × LoPE			0.017			0.054
			(0.45)			(0.93)
Abn. Accruals	-0.063			0.071		
	(-0.62)			(0.47)		
Disc Sales						
Abn. Prod Cost		-0.001			-0.002	
		(-0.02)			(-0.02)	
Abn. Disc Exp			-0.007			-0.042
			(-0.31)			(-0.91)
LoPE	-0.042	-0.137**	-0.039	-0.060	-0.107	-0.052
	(-1.02)	(-2.20)	(-0.61)	(-0.80)	(-0.84)	(-0.60)
GP Country FE	Y	Y	Y	Y	Y	Y
Vintage FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	193	99	132	169	89	117
R-sq	0.320	0.435	0.328	0.302	0.513	0.468
Cluster	GP	GP	GP	GP	GP	GP

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Internet Appendix to:

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. **??** for a list of variable definitions related to private equity.

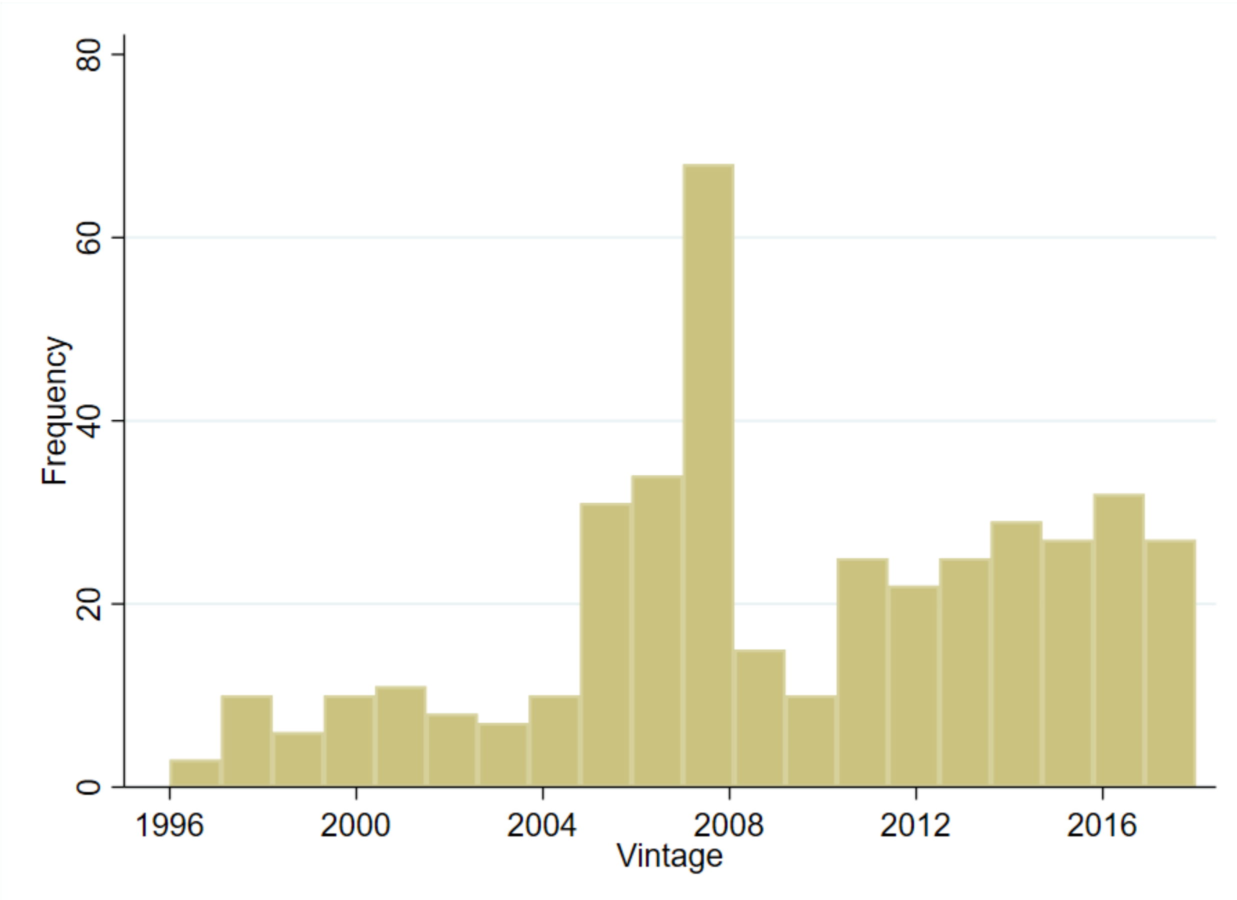

Figure IA2: **PSM matching procedure**

This figure explains the PSM matched sample in comparison with the full sample. The first graph depicts the sample composition of the whole sample; the second graph depicts the sample composition of the PSM-matched sample. Yellow boxes indicate fundraising periods and light blue boxes indicate periods without fundraising. PSM sample keeps one (or three for portfolio firm-sample) control firm-quarter (i.e. fund-quarter that is not fundraising) for each treated firm-quarter (i.e. fundraising quarter).

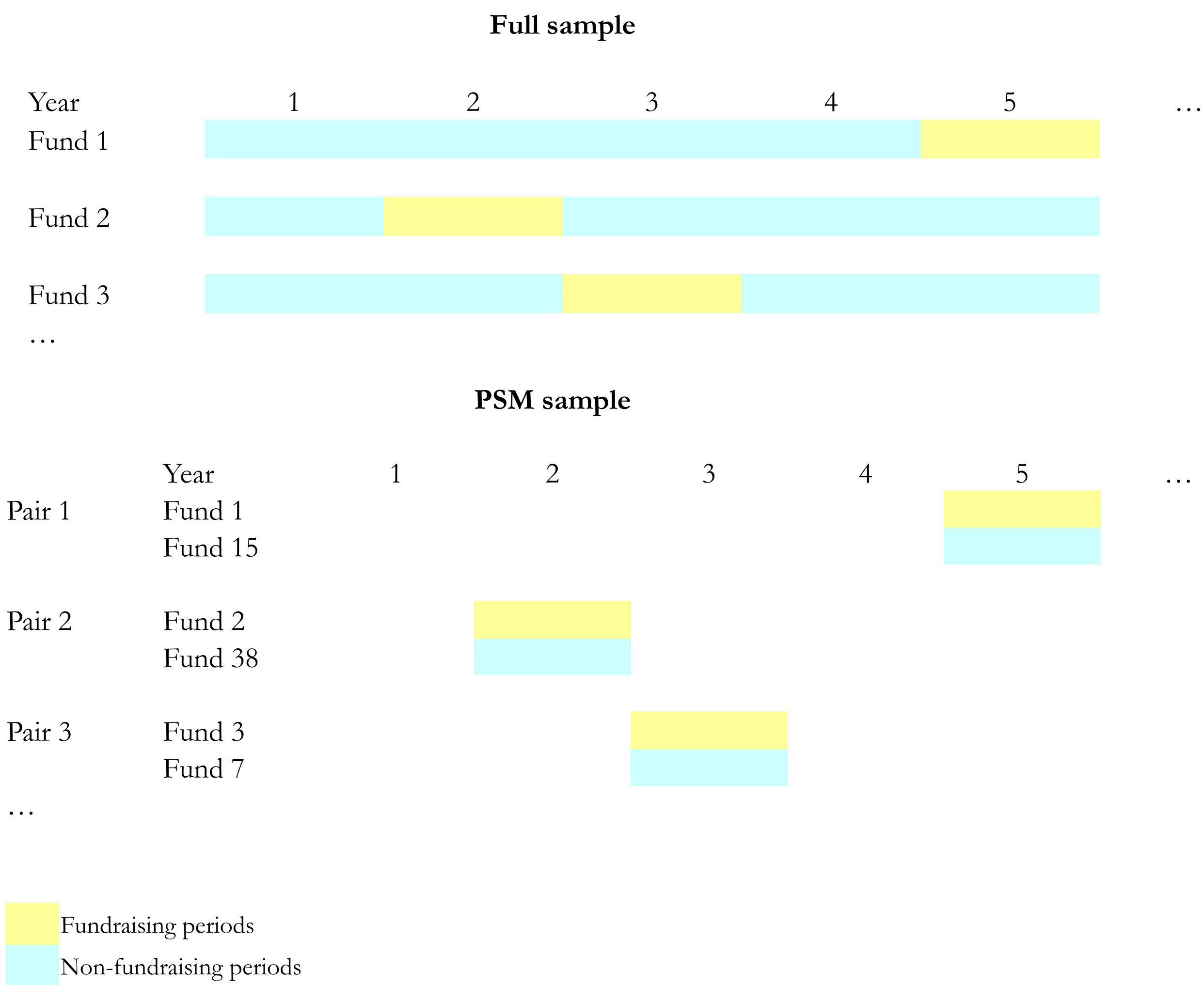

Table IA1: **Keeping fourth quarters**

This table estimates Equation 6.1 (Panel A) and Equation 6.2 (Panel B) after keeping fourth calendar quarters. See table A1 for a complete list of variable definitions. All continuous variables are winsorized at the 1% level. *,**, 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	0.190	0.239	-0.140*	-0.154**
	(1.38)	(1.61)	(-1.73)	(-2.16)
Controls	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y
N	505	584	1,497	1,645
R-sq	0.775	0.744	0.779	0.821
Clustering	Fund	Fund	Fund	Fund

Panel B: Portfolio-firm level tests

	Low reputation			High reputation		
	(1)	(2)	(3)	(5)	(6)	(7)
Dependent variable: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
FundraiseFlag	0.066*	-0.226	0.360	-0.025	-0.124	-0.124
	(1.76)	(-1.06)	(1.24)	(-1.30)	(-0.96)	(-1.15)
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	903	562	312	3,764	1,862	1,056
R-sq	0.754	0.867	0.670	0.502	0.650	0.555
Clustering	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm

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 6.1 (Panel A) and Equation 6.2 (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. All continuous variables are winsorized at the 1% level. *,**, 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 variable:	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)
Controls	Y	Y	Y	Y
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)	(5)	(6)	(7)
Dependent variable: Abn.	Accruals	Prod Cost	Disc Exp	Accruals	Prod Cost	Disc Exp
FundraiseFlag_CF	0.043**	-0.201	0.131	-0.011	-0.016	0.015
	(2.07)	(-0.93)	(1.34)	(-0.77)	(-0.25)	(0.18)
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
Pf Firm Ind-Year FE	Y	Y	Y	Y	Y	Y
N	3,652	2,263	1,267	14,710	7,420	4,278
R-sq	0.723	0.840	0.639	0.488	0.564	0.519
Clustering	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm	Fund, Pf Firm

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

This table uses the dependent variable in Equation 6.1 winsorizing at the 1% level instead of 5%. Columns (1)-(2) ((3)-(4)) use low reputation (high reputation) fund samples. See Table A1 for a complete list of variable definitions. All 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)
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 6.2. The table reports results for portfolio firms owned by low reputation GPs. See Table A1 for a complete list of variable definitions. All continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: Abn.	(1) Accruals	(2) Prod Cost	(3) 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: **Abnormal discretionary sales as dependent variable**

This table reports regression results using abnormal discretionary sales from Stubben (2010) as the dependent variable and re-estimate Equation 6.2. The table reports results for portfolio firms owned by low reputation GPs. See Table A1 for a complete list of variable definitions. All 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)
Dependent variable: Abn.	Disc Sales	Disc Sales
FundraiseFlag	0.025**	-0.013***
	(2.03)	(-2.71)
Controls	Y	Y
Fund FE	Y	Y
Year-Quarter FE	Y	Y
Pf Firm FE	Y	Y
Pf Firm Country-Year FE	Y	Y
Pf firm Ind-Year FE	Y	Y
N	4,824	21,283
R-sq	0.548	0.380
Clustering	Fund, Pf Firm	Fund, Pf Firm

Table IA6: **Propensity-score-matching results - fund-level**

This table presents results for propensity-score-matching procedure at the fund-level. Panel A reports probit regression that regresses variable *FundraiseFlag* (indicator that equals one if the fund-quarter is fundraise quarter, and zero otherwise) on performance, natural log of number of portfolio firms in a fund-quarter, and natural log of fund age. With this regression, I match three nearest neighbors within 1 standard deviation caliper. Panel B presents t-test results for control variables. All continuous variables are winsorized at the 1% level. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Probit regression results

	(1)
Dependent variable:	FundraiseFlag
ln(# of portfolio firms)	0.050**
	(2.07)
ln(Fund age)	-0.607***
	(-17.60)
NAV	0.981***
	(15.36)
Constant	-0.895***
	(-13.69)
N	8,763
Pseudo R-sq	0.083

Panel B: T-test between treated and control firms

	Control		Treat		
Variables	N	Mean (1)	N	Mean (2)	(1) - (2)
ln(# of portfolio firms)	172	1.576	184	1.659	-0.083
ln(Fund size)	172	6.309	184	6.273	0.037
ln(Fund age)	172	1.62	184	1.661	-0.041
ln(GP age)	172	2.593	184	2.523	0.069
NAV	172	0.631	184	0.685	-0.054*

Table IA7: **Regressions using PSM sample - portfolio firm-level (matched with PE-owned portfolio firms)**

This table shows results for PSM procedure. Panel A shows probit regression results used to obtain matching control firms. Panel B presents T-test results of difference in means between treated and control firms. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Probit regression results

	(1) FundraiseFlag
ln(# of portfolio firms)	0.025**
	(2.11)
ln(Fund age)	-0.639***
	(-30.20)
NAV	0.783***
	(20.98)
Constant	-0.715***
	(-16.35)
N	29,085
Pseudo R-sq	0.067

Panel B: T-test between treated and control firms

	Control		Treat		
Variables	N	Mean (1)	N	Mean (2)	(1)-(2)
ln(# of portfolio firms)	462	1.617	462	2.075	-0.458***
ln(Fund size)	462	6.142	462	6.205	-0.063
ln(Fund age)	462	1.784	462	1.768	0.016
ln(GP age)	462	2.645	462	2.607	0.038
NAV	462	0.633	462	0.651	-0.019