Catering and Return Manipulation in Private Equity*

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Abstract

We provide evidence that private equity (PE) fund managers manipulate returns to cater to their investors. Using a large dataset of PE real estate funds, we show PE fund managers overstate returns if they oversee a larger share of their investors' assets, and doing so has a more significant impact on investors' reported returns. Additional results are inconsistent with models in which investors punish or are deceived by manipulations. In contrast, our results highlight an underlying tension in PE performance: the "phony happiness" some PE investors receive from overstated and smoothed interim returns due to agency frictions within their organizations.

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Private Equity (PE) plays an increasingly central role in the portfolios of institutional investors and the overall economy, raising more than $5 trillion globally over the period 2017-2021 (Bain 2022). Recently, regulators suggest that some investors make these commitments based on reported returns that are boosted or otherwise manipulated by some PE managers.[1] Several recent studies investigate this "window dressing" in PE, similarly suggesting that return manipulations are an attempt to fool potential investors.[2] Yet, PE investors are sophisticated, raising an alternative possibility that PE fund managers may manipulate returns because some PE investors prefer boosted interim returns.

In this paper, we provide empirical support for this alternative view of PE fund manager window dressing based on the idea that some PE fund managers manipulate interim returns in a manner consistent with their investors' desires. Similar to the idea that banks design financial products to cater to yield-seeking investors (e.g., Célérier and Vallée (2017)) or firms issue dividends to cater to investor demand for dividend payments (e.g., Baker and Wurgler (2004)), we argue that PE fund managers boost interim performance reports to cater to some investors' demand for manipulated returns. We offer a simple explanation for this catering phenomenon in PE: some PE investors face agency frictions within their organizations that make manipulated interim returns attractive.

Our catering view of return manipulation is related to the emerging view that PE commitments are driven in part by the slowly updated, or "smoothed," nature of PE returns. Cochrane (2022, P. 8) asserts:

> *Why do so many institutions, like our endowments, prize assets like private equity, venture capital, and real estate with no clear market values? Well, perhaps they like those assets precisely because the assets are hard to mark to market, easy to just pay out 5% of a made-up value, not to sell in a panic, and not fire the asset manager based on an irrelevant price—or rather a price that is only relevant when combined with the state variable, which accountants and oversight committees are no better at evaluating than our hypothetical spouse.*

Bob Maynard, the Chief Investment Officer of Idaho's Public Employee Retirement System,

[1] See recent coverage of the U.S. Security and Exchange Commission's investigation of PE reporting practices and fees (https://on.wsj.com/3KeIEuF and https://on.wsj.com/3Jnr3PU).

[2] For example, Barber and Yasuda (2017) show that buyout and venture fund performance peaks during fundraising, especially among managers with poor track records, and Brown, Gredil, and Kaplan (2019) show that managers that overstate asset values often fail to raise follow-on funds.

further describes these incentives for investing in private equity in a CalPERS public meeting (Maynard 2015, 1h:28m:50s). He states,

> *We did know that our actuaries and accountants would accept the smoothing that the [Private Equity] accounting would do. It may be phony happiness, but we just want to think we are happy and they actually do have consequences for actual contribution rates we are going to be able to put in place[.] Even if [Private Equity] just gave public market returns, we'd be in favor of it because it has some smoothing effects on both reported and actual risks.*

We think of this "phony happiness" as the propensity for some PE investors (Limited Partners; LPs) to accept or even seek out PE fund managers (General Partners; GPs) that provide manipulated interim returns.[3] PE returns are calculated using valuations of illiquid, non-traded assets and interim cash flows. These features result in artificially lower correlations with public asset classes and, importantly, are influenced by GPs. If a GP boosts or smooths returns, perhaps by strategically timing asset acquisitions and dispositions or by misstating the values of underlying assets, investment managers within LP organizations can report artificially higher Sharpe ratios, alphas, and top-line returns, such as IRRs, to their trustees or other overseers. In doing so, these investment managers, whose median tenure of four years often expires years before the ultimate returns of a PE fund are realized, might improve their internal job security or potential labor market outcomes.

Return manipulations can also produce significant paper wealth for LPs. For U.S. public pension LPs, this can marginally improve funding statuses or alter required contribution funding rates. Because PE returns are often quoted as IRRs, such return manipulations can permanently window dress the PE fund's end-of-life returns. Moreover, a GP's decision of when to sell illiquid assets, and thereby selectively reveal the market prices of these assets,

[3] In a similar spirit, Asness (2019) contends that PE illiquidity may be "a feature rather than a bug," perhaps even more so in real estate (footnote 14). Gupta and Van Nieuwerburgh (2021) suggest that the equilibrium illiquidity premium in PE might be negative to reflect the "convenience" of illiquidity for public pension PE investors. Baz, Davis, Han, and Stracke (2022) estimate that a public market index requires an additional six percentage points of annual returns to match the Sharpe ratios of smoothed private market returns. Riddiough (2022) argues that U.S. public pensions accept a return discount of about three or four percentage points annually to access a "veil of illiquidity" that comes from investing in commercial real estate through PE funds, rather than listed real estate, such as Real Estate Investment Trusts (REITs). Stafford (2022) shows that hold-to-maturity accounting, which mimics slow marking to markets, reduces the standard deviation of returns for a public market portfolio that replicates buyout asset selection from 24% to about 7%. Cliff Asness refers to the smoothing phenomenon as "volatility laundering." (See https://bit.ly/3HIFm1M.) Korteweg and Westerfield (2022) offer a similar synthesis in the context of LP allocations.

may be attractive to investors insofar as doing so "insulates" LP investment managers from temporary dislocations in market prices. However, while manipulated returns can potentially benefit individual LP investment managers, they may also distort allocations away from perhaps a more optimal risk-return strategy for their longer-horizon principals (such as taxpayers and pension beneficiaries), which can have potentially negative and non-trivial real effects.

Our empirical setting involves a large sample of private equity commercial real estate (PERE) funds and investors spanning 2001 to 2019.[4] PERE is ideal for testing our catering proposition. PERE funds have typically underperformed other alternative asset classes and various market indices, but nevertheless have grown to be the second-largest PE asset class by commitments (e.g., Andonov, Kräussl, and Rauh (2021) and Gupta and Van Nieuwerburgh (2021)). Importantly, PERE holdings are similar to those of easily accessible, yet more visibly volatile, public market alternatives (Real Estate Investment Trusts; REITs). Despite some structural and compositional differences, listed real estate provides commercial real estate exposure of analogous quality with greater liquidity and lower search costs and fees (e.g., Ghent (2021)). However, consistent with a preference for GPs' influence on markings and exit timings, LPs investing in real estate overwhelmingly allocate to private market alternatives, such as PERE, rather than higher performing and more transparent marked-to-market REITs.[5]

We start our analysis by measuring return manipulation by PERE GPs. We calculate return manipulation as the effect of raising a follow-on fund on reported IRRs using a staggered difference-in-differences (DiD) design. The intuition is that a successful fundraise "shocks" manipulation incentives: GPs might manipulate IRRs to attract investors, but after investors commit capital to the follow-on fund, the primary incentive to overstate interim returns decreases.[6] Because IRRs reported to LPs are a function of both interim cash-flows

[4]Although we focus our analysis on PERE funds, we also find similar performance patterns for buyout and venture funds in our internet appendix.

[5]Approximately 80% of pensions invest in real estate through PERE vehicles but only 30% invest in real estate through listed funds such as REITs (see the 2016 report by Preqin https://bit.ly/3bMnesf). Additionally, listed REITs account for only 14% of public pension real estate allocations (see the 2021 study by CEM Benchmarking https://bit.ly/3zLN2gf).

[6]We address numerous potential econometric and identification concerns, including using recent DiD innovations, conducting numerous falsification and other tests around fundraise timing, and highlighting

and underlying fund Net Asset Values (NAVs), differential trends in IRRs around fundraising can capture a broad scope of manipulations, related to not only NAV misstatements but also the timing of asset disposals and acquisitions. This is essential to our "demand-side" proposition because LPs may react to multiple forms of manipulation.

We find that GPs overstate net annual IRRs around fundraising by 470 basis points (bps), on average. This estimated treatment effect is economically meaningful, equaling approximately 50% of the median IRR reported during fundraising and coming close to the average final net IRR of 5.45% in our sample. Our graphical evidence shows parallel pre-fundraising trends and a sharp monotonic decline in reported IRRs after fundraising. Our results are robust to an extensive array of falsification and robustness checks, including out-of-sample tests with quarterly cash-flow data from an alternate data source.

Turning to the "demand-side" of return manipulation, we develop several measures of the incentive for a GP to boost returns based on the elasticity of investor benefits from higher interim fund returns. Our primary measure of this incentive is the average fraction of investor assets allocated to a particular fund, which we refer to as "LP performance sensitivity." In the spirit of Bergstresser, Desai, and Rauh (2006), our measure captures whether one fund is, on average, relatively more important for the portfolio level returns of its LPs than another.

We find that cross-sectional variation in LP performance sensitivity strongly predicts GP return manipulations. GPs tend to manipulate returns if they manage a larger share of their investors' assets. We estimate that IRR return manipulations average 640 bps among funds with above-median investor performance sensitivity scores but an insignificant 110 bps among funds with below-median investor performance sensitivity scores. Although an LP's allocation to a single fund usually cannot comprise a large portion of the LP's assets, we estimate that these manipulations noticeably distort LP-level IRRs for LPs of high elasticity funds. Manipulations add about 24 basis points of annualized returns for the average LP in high-elasticity funds. In contrast, manipulations only add about 0.1 basis points of annualized returns for LPs in low-elasticity funds. Taken together, our results suggest that some GPs respond to LP "demand" for boosted IRRs. Further supporting our

features of fund governance documents and industry norms that help ensure the timing of fundraising events are rationally anticipated by GPs.

catering perspective, the average GP that boosts IRRs also successfully raises capital for a follow-on fund. This finding is consistent with the view that LPs do not punish GPs for manipulating IRRs by refusing to commit capital to subsequent funds.

Importantly, our results also highlight that only some forms of manipulation are acceptable to LPs. Similar to Brown, Gredil, and Kaplan (2019), we find that GPs do not appear to manipulate IRRs by directly overstating NAVs around fundraising.[7] However, our broader definition of return manipulation allows us to show that GPs instead employ several timing strategies to manipulate IRRs. Funds that manipulate returns tend to "sell winners and hold losers," delay mark-downs until after fundraising, and exit their best-performing properties immediately before raising capital for a follow-on fund. These results are consistent with several manipulation mechanisms proposed by Gompers (1996), Phalippou (2008), Lopez-de-Silanes, Phalippou, and Gottschalg (2015), Barber and Yasuda (2017), and Chakraborty and Ewens (2018). We further provide novel evidence that return manipulations are partially explained by GPs delaying performance fees. This finding is consistent with a previously unexplored strategic fee timing manipulation.

It is also informative to relate our catering results to other manipulation incentives GPs may have. GPs might manipulate returns if their LPs are less sophisticated or have limited monitoring capabilities or incentives. Additionally, GPs might inflate returns to match differential LP expectations about their final returns due to their reputation (Barber and Yasuda 2017) or underlying asset risk. In the cross-section, measures of other manipulation incentives are associated with IRR manipulations but not after conditioning on LP performance sensitivity. These results show that our catering view is distinct from several other manipulation incentives.

Lastly, we examine an agency-based mechanism for our catering phenomenon. Dyck, Manoel, and Morse (2021) suggest that U.S. public pension boards "risk up" their portfolios to improve their funding statuses (Andonov, Bauer, and Cremers 2017) rather than disclose funding shortfalls to legislatures. Dyck et al. (2021) also show that public pension boards are reluctant to pay their Chief Investment Officers (CIOs) market salaries because doing

[7]NAV manipulation opportunities are generally less available for commercial real estate valuations than for private company valuations.

so might upset their plan beneficiaries. In equilibrium, agency costs are thus highest among pension plans that are underfunded and that pay their CIOs relatively less. To examine these frictions, we link annual reports by U.S. public pensions with our primary measure of LP return sensitivity at the LP level. We find that underfunded pension plans are more likely to allocate a higher fraction of their assets to a given PERE fund. Similarly, public pension CIO compensation is negatively related to the proportion of pension assets allocated to a given PERE fund. These results suggest that agency frictions within public pensions are associated with determinants of GP return manipulation decisions.

Our results contribute to several literature streams. We show that LP return elasticities, as measured by the average effect of a PERE fund's returns on its LPs' portfolio returns, are positively associated with GP return manipulations. These findings introduce an alternative view of return manipulation based on the idea that some PE fund managers manipulate interim returns in a manner consistent with their investors' desires. These results complement research on catering to investors (e.g., Baker and Wurgler (2004), Baker, Greenwood, and Wurgler (2009), Gennaioli, Shleifer, and Vishny (2012), and Célérier and Vallée (2017)).

Our "demand-side" analysis also offers insights into the growing debate on the cause of the rapid increase in PE allocations. We highlight that a GP's ability to manipulate returns can be a positive feature rather than a bug from the LP's perspective—potentially attracting allocations, insofar as the equilibrium level of window dressing is positively correlated with the agency issues that stimulate LP demand for return manipulation. This finding complements studies of agency frictions between GPs and LPs (e.g., Robinson and Sensoy (2013)). An important component of our demand-side analysis is that the ability of a PERE fund to selectively reveal market prices of underlying illiquid assets over time may be attractive to investors. These findings complement research that emphasizes the ability of financial intermediaries to "insulate" investors from temporary dislocations and fluctuations in market prices (e.g., Cherkes, Sagi, and Stanton (2008), Hanson, Shleifer, Stein, and Vishny (2015), and Chodorow-Reich, Ghent, and Haddad (2020)).

Lastly, our findings contribute to an extensive literature that studies return manipulation in delegated asset management (e.g., Lakonishok, Shleifer, Thaler, and Vishny (1991), Chevalier and Ellison (1997), Bollen and Pool (2009), and Agarwal, Gay, and Ling (2014)). We are the first to provide evidence of window dressing in PERE funds and document the relative importance of different manipulation channels. Gompers (1996), Jenkinson, Sousa, and Stucke (2013), Barber and Yasuda (2017), Chakraborty and Ewens (2018), Brown et al. (2019), and Hüther (2021) examine window dressing among buyout and venture PE funds and emphasize the role of GP characteristics. Our findings are closely related to the result reported by Brown et al. (2019) that NAV manipulation is likely noticed by investors. However, our results differ in that LPs accept, rather than punish, return boosting when done through channels other than NAV overstatement.

1 Data

In this section, we describe the data and summary statistics relevant to our analysis. As background, PE investing occurs primarily through PE funds. Funds are typically closed-end, limited partnerships with a stated life of eight or more years. PE firms sponsor the fund and serve as general partners. High net-worth individuals and large institutional investors serve as LPs and contribute most of the capital. In return, LPs receive net-of-fee proceeds from investments made by GPs. Funds are governed by a Limited Partnership Agreement (LPA), which determines fee arrangements and specifies solutions for general conflicts of interest. GPs embark on fundraising campaigns every few years, beginning the process before the current fund expires and its actual performance is realized.

1.1 Sample Construction

To investigate the influence of PERE investors on return manipulations, we obtain quarterly data on the performance of PERE funds from Cambridge Associates (CA) and data on institutional investors from Preqin. Additionally, to examine determinants of fund allocations, we supplement Preqin investor data with public pension characteristics from the Public Plans Database (PPD) and the annual compensation of pension plan managers.

CA is one of the largest providers of investment consulting services for PE investors (with a focus on family offices, foundations, and endowments). Brown, Harris, Jenkinson, Kaplan, and Robinson (2015) show CA data contains 18% more buyout and 22% more venture funds with performance data relative to the next largest provider, Burgiss, for the period 1984-2010. Additionally, Harris, Jenkinson, and Kaplan (2014) show that vintage year performance estimates are consistent across CA and Burgiss for buyout and venture funds, mitigating some selection bias concerns. CA obtains fund performance data directly from the quarterly reports provided by GPs to their LPs and validates these reports—often by contacting fund managers to resolve any discrepancies.[8] This ensures the interim data are of high quality. CA also (1) provides confidentiality to managers by only unlocking data to identified data subscribers, (2) requests information from all PERE funds of which it is aware, and (3) reports that less than 1% of data in any performance quartile is plausibly affected by survivorship bias.

The CA dataset includes annualized Internal Rates of Return (IRR), Total Value to Paid-in Capital (TVPI), Distributions to Paid-in Capital (DPI), and percent called quartiles at a quarterly frequency for 950 PERE funds active in the period 2006 to 2019.[9] Variables reported in CA, such as IRR and TVPI (also called a multiple on invested capital), are forward looking measures that reflect "to-date" distributions to LPs as well as expected distributions over the funds' lives as of a given quarter. These metrics are quite speculative early in each fund's life given limited capital deployment, uncertain performance, and few, if any, cash flow distributions to investors. Importantly, although the reported IRR and TVPI become more representative of what the final IRR and TVPI will be as time goes by, they can still be easily manipulated during the period of time in which capital is being raised for a follow-on fund. All performance metrics are reported net of fees. Additionally, CA supplements performance data with fund-specific characteristics such as size and strategy.

For each fund in the CA database, we manually identify the same fund and GP in the Preqin universe to verify the dates of new fund formation, the sequence of funds operated by a particular GP, and the identities of a portion of the LPs that invested in each fund.

[8]Discrepancies among reports within a fund can arise for several reasons. For example, LPs may agree to different fee terms (Begenau and Siriwardane 2022). Additionally, GPs may use alternative structures, such as parallel funds, co-investments, or feeder funds, to accommodate differential allocation capabilities or tax incentives.

[9]CA does not provide quarterly cash flows or NAVs. As a result, we leverage the algebraic relationships between TVPI, DPI, and percent called to impute quarterly cash flows and NAVs. We discuss our method further in our internet appendix.

The Preqin PERE universe is advantageous for our study given the breadth of its coverage and unique ability to provide LP identities. The Preqin PERE database contains 11,601 funds, sponsored by 3,125 GPs, that received 27,419 known commitments from 3,766 LPs between 1969 and 2021. Commitment-level data points include the LP, investor class (e.g., public pension or sovereign wealth fund), identifying information for the fund receiving the investment, and frequently the level of capital that the LP committed to the fund.

We obtain additional data for U.S. public pension LPs from two sources. First, we gather data from the PPD. The PPD is based on the annual reports filed by 210 public pension funds in the United States from 2001 to 2020 and covers 95% of state and local pension assets and members in the U.S. over the same time period. For each pension fund, we manually identify the plan sponsor in Preqin. If a pension fund has a separate board that makes investment decisions, we pool the fund assets, liabilities, and other data points at the board level, reflecting the economics of allocation responsibilities (Andonov, Hochberg, and Rauh 2018).[10] Second, we collect compensation data (annual salaries and bonuses) for pension fund CIOs for the period 2001-2018, obtained through FOIA requests by Lu, Mullally, and Ray (2021). Our underlying pool of CIOs follows that of Lu et al. (2021), with the average CIO having a six year tenure and the median CIO having a four year tenure. We map CIO compensation to PPD data and hence to Preqin and CA.

We limit our analysis to closed-end PERE funds with inception dates from 2001 to 2014, an ending date that gives GPs at least seven years to raise a follow-on fund and at least five years to unwind any window dressing.[11] We additionally restrict our sample to commercial real estate (CRE) funds. This filter ensures that PERE funds in our sample follow; opportunistic, value added, distressed, core, and core-plus strategies. Lastly, we require that funds have at least 20 quarters of consecutively reported IRRs and that this interval of 20 quarters includes quarters before, during, and after the estimated fundraising

[10] For example, the Minnesota State Board of Investment manages assets for multiple pensions funds including the Teachers Retirement Association of Minnesota and the Minneapolis Employees Retirement Fund.

[11] For a given fund, CA begins reporting from the quarter of legal inception, rather than from the date of the first capital call, as is common in other PE databases. We find that this distinction is immaterial for our results. Nonetheless, in our main analysis, to improve comparability with other data sources we start tracking performance for each fund at the first capital call date (i.e., the first quarter in which performance metrics are not missing and there is evidence that the fund has made an investment).

quarter. Our resulting sample contains 448 funds, managed by 208 PERE firms, accounting for almost \$350 billion in committed capital. This sample represents about 30% of all allocations to closed-end private CRE funds during our sample period.

For our cross-sectional tests involving LP fund commitments, we exclude 128 CA funds where the known commitments by the fund's LPs account for less than 5% of the fund's size. The resulting sub-sample contains 320 funds, managed by 148 PERE firms, accounting for almost \$300 billion in committed capital. Of our 320 funds, 249 funds have at least one public pension LP with a known allocation mapped to the PPD.[12]

We then take considerable care to ensure fund sequencing and fundraise timing are correct. As will become clear, doing so is important for our measurement of return manipulation. Our fund sequencing relies on the extensive Preqin universe and follows Brown et al. (2019). A follow-on fund is the next closed-end CRE fund, raised by the same manager, at least three years after a fund's first capital call.[13] Although GPs are sometimes allowed to raise capital for follow-on funds as early as one to two years into the predecessor fund's life, the three-year waiting period helps ensure interim returns for the predecessor fund impact the fundraising outcome for the potential successor fund. After creating a baseline sequence, we manually confirm fundraising outcomes for each fund in CA, accounting for rarities such as mergers and funds not tracked by Preqin. The follow-on success rate is about 82% for CA alone and almost 93% after Preqin sequencing.

After sequencing the funds in our sample, we define the fundraising quarter to be the quarter of the first capital call of the follow-on fund, following Barber and Yasuda (2017) and Brown et al. (2019).[14] Because GPs do not call capital until the follow-on fund is

[12]For comparison, Preqin's parallel PERE sample only contains 273 CRE funds vintaged between 2001 and 2014 with sufficient data. 131 of these Preqin funds with cash-flow data are also in the CA sample and 243 have sufficient commitment data. In our internet appendix, we find our results are robust to using the smaller Preqin sample and permutations thereof. However, we rely on the larger CA sample because the cross-sectional tests are more powerful.

[13]For example, if the vintage year of the current fund is 2008, the earliest possible vintage for a potential follow-on fund is 2011. Accordingly, a minimum of eight quarters may elapse between funds by our implementation. Our results are robust to instead using a strict cutoff of 12 quarters or various permutations of the follow-on fund definition.

[14]If the follow-on quarter is missing and the fund has a follow-on fund, then we set the fundraising quarter as the median number of quarters since the first capital call for all successful fundraisers in the same vintage. This applies to 100 funds in our sample. Our results are robust to dropping these funds or using the average rather than the median.

of sufficient size, the quarter of the first capital call typically marks the end of the most intense fundraising efforts. However, in our internet appendix, we also show our results are robust to uniformly shifting the fundraising date up to four quarters earlier and also to calculating results at an annual rather than quarterly unit of time, reflecting the facts that LPs may receive reports with a lag and that fundraising can last longer than a single quarter. Figure A1 plots our sample composition and associated fundraising events in calendar time split between funds that have raised, and those that have not yet raised, a follow-on fund. Fundraising events are relatively diffuse, with an average of 8.6 per quarter over the period 2006-2019. On average, 309 funds report IRR in a given quarter.

1.2 Summary Statistics

Table 1 describes the composition of the 448 funds and 1,372 LPs active between 2001 and 2019 in our sample. 33% of funds are fully liquidated as of the end of 2019, 90% of funds follow an opportunistic or value-add strategy, and 75% of funds acquire multiple property types. Roughly two-thirds of the funds focus exclusively on domestic properties. 56% of LPs are private-sector pensions (e.g., AT&T Pension Fund) or public pensions (e.g., CalSTRS), with public and private sector funds of equal importance. 92% of LPs are domiciled in North America. The Preqin CRE column tabulates characteristics for all PERE funds and LPs in the Preqin universe active during our sample period.[15]

Table 2 summarizes the main variables used in our analysis. Panel A describes the observations in each fund-quarter cell. CA censors the first year of reported IRRs and interim IRRs with absolute values exceeding 100% because they are typically meaningless and disregarded by LPs. Our results for other variables are unchanged if we limit observations to only cells where IRRs are available. We calculate Brown et al. (2019) interim (to-date) Public Market Equivalents (PMEs) each quarter using the FTSE Nareit U.S. equity REITs

[15] A relevant selection concern in our data comes from the higher fundraising success rate of CA funds relative to that of the 3,972 CRE funds in the Preqin database (93% to 74%). This selection concern works against finding window dressing if funds with higher expected fundraising success face weaker manipulation incentives. Nonetheless, our results are qualitatively unchanged after oversampling failed fundraisers. The same selection concerns are also present in the smaller Preqin sample (92% fundraising success rate), suggesting potential biases come from GPs and LPs that reveal their performance data to commercial data providers rather than CA's sourcing process.

index, which excludes mortgage REITs. DPI and its complement, Residual Value to Paid-in-Capital (RVPI), sum to TVPI and respectively equal the value of cumulative distributions made to LPs and the current value of all remaining investments within a fund (NAVs), scaled by the value of called capital, as of a given quarter.

The average quarterly to-date performance measures include; IRR of 2.15%, TVPI of 1.10, DPI of 0.47, and RVPI of 0.63. Additionally, the average to-date PME is 0.87. Despite the average fund having returned 47% of committed capital to LPs as of a given quarter, average interim IRRs are particularly low, due primarily to the inclusion of several funds that suffered complete losses (IRR of -100% and TVPI of zero).

Panel B describes the characteristics and performance of funds in our sample. There is significant skewness in capital allocations, reflected in both fund size and the number of previous funds. The median fund reports a final IRR of 7.61% and PME of 0.91, after fees. This is similar to statistics reported for PERE funds by Andonov et al. (2021) and Gupta and Van Nieuwerburgh (2021) and broadly consistent with a tendency for real assets held in closed-end private fund structures to underperform public market benchmarks.[16]

Panel C describes LPs and commitments in our sample aggregated at the fund level. On average, 38% of investments in a fund are re-commitments. The sum of known commitment values equals 22.69% of committed capital for the average fund, indicating several LPs and commitment values are missing from each fund. Unknown LPs and commitments distort the concentration of fund commitments, as measured through the Herfindahl-Hirschman Index (HHI) index.

Accordingly, to better measure the concentration of LPs within a fund, we develop and apply a correction to jointly estimate the number of fund LPs and the level of unknown commitments. We first assume all unknown commitments equal the average of known commitments within a fund, $\bar{c}$. If the sum of allocations is still less than the fund size, we add new LPs, assuming each allocates $\bar{c}$, until the sum of total investments equals the fund size. If an additional LP pushes the sum of commitments over the fund size, we evenly distribute the remaining unaccounted-for commitments among known LPs with missing allocations. We

[16] If we restrict the sample to the 411 funds with a final IRR above zero, then the average final IRR is approximately 10% and the average final PME is approximately 1.05. Our results our similar if we focus only on this subsample.

apply this procedure to the subset of 320 funds where at least 5% of fund size is accounted for. In doing so, we estimate that an average fund has eight missing LPs and that a median fund has a commitment HHI of about 650, where HHI is defined as the sum of the squared commitment shares for each fund LP (ranging from 0 to 10,000). We include a closed-form estimation procedure and a validating simulation in the internet appendix.[17]

Lastly, the data presented in Panel D describes the 93 U.S. public pension LPs in the PPD that made 1,076 allocations to PERE funds in our sample at the pension-year level. The average CIO earns $221,903 (bonus plus salary) annually, and the average pensioner receives an annual salary of $50,011. The panel shows that the average plan is underfunded (78%). In untabulated results, we find that the median plan has actuarial assets of about $16 billion and actuarial liabilities of about $19 billion.

2 Descriptive Evidence of IRR Manipulations

A standard approach for examining return manipulations in PE funds starts by tracking the evolution of performance metrics around fundraising events. GPs often attempt to raise capital for successor funds within the first five years after launching their current fund. We refer to this period, starting in year three when reported IRRs are relatively more meaningful, as the "anticipated fundraising window." LPs may use interim performance metrics to decide whether to commit capital to a follow-on fund. This may incentivize GPs to boost interim IRRs while raising capital for a follow-on fund. In fact, interim performance metrics are positively correlated with fundraising success (e.g., Chung, Sensoy, Stern, and Weisbach (2012), Hochberg, Ljungqvist, and Vissing-Jørgensen (2013), and Barber and Yasuda (2017)).

Figure 1 shows that reported net-of-fee IRRs peak within the anticipated fundraising window. The average GP reports a net IRR of around 7% during this period, while the median GP reports a net IRR of around 10%. Figure 2 plots the average and median net IRRs in event time around the fundraising quarter for the funds in our sample that raised a subsequent fund. Consistent with Figure 1, the peak during the anticipated fundraising

[17] Although we rely on our imputation procedure to calculate several subsequent results involving commitment data, it is not necessary to obtain our main findings. In our internet appendix, we show that our headline results are robust to instead using only observed commitments and LPs.

window coincides with fundraising events. Before fundraising, reported IRRs increase monotonically and peak around 7% for the average fund and 10% for the median fund during the fundraising quarter. After fundraising, the average IRR declines to 6.7%, 6.5%, and 5.9%, over the subsequent one, two, and three years.

These patterns in CRE fund performance reports are also consistent with those reported in recent studies of performance manipulations in buyout and venture funds (e.g., Barber and Yasuda (2017), Chakraborty and Ewens (2018), Brown et al. (2019), and Hüther (2021)). However, performance declines are a necessary but not sufficient condition for identifying return manipulation. In what follows, we employ a research design that exploits institutional features of PE fundraising to measure return manipulation.

3 Research Design

We measure return manipulation using a staggered difference-in-differences (DiD) research design that compares the reported net-of-fee IRRs of managers that have raised a follow-on fund (the "treatment" group), to the reported net-of-fee IRRs of managers who have either not yet raised or ultimately failed to raise a follow-on fund (the "control" group). This treats fundraising events as a "shock" to manipulation incentives, allowing us to determine whether the returns of one fund were manipulated, but the returns of another fund were not.

The intuition behind our research design is as follows. Although PE fund managers may manipulate interim returns to attract investors, after investors commit capital to the follow-on fund, the incentive to inflate interim returns decreases. This is clearly captured by differential trends in to-date IRRs.

Throughout, we use the Borusyak, Jaravel, and Spiess (2021) DiD "imputation" estimator to compute the effect of fundraising on IRR and visually inspect for pre-trends. Unlike a standard two-way fixed effects OLS regression, this estimator is robust to treatment effect heterogeneity and avoids issues of spurious identification, contaminated fixed effects, and negative weights (e.g., de Chaisemartin and D'Haultfœuille (2020) and Sun and Abraham (2021)). This approach first fits a regression of reported fund performance each quarter (y_{it}) on fund and calendar time fixed effects, as well as fund-quarter varying controls, in the set of untreated fund-quarter observations (i.e., quarters in which the GP has not yet called capital for a follow-on fund). We then use the coefficients from the first-stage regression to predict the counterfactual performance for treated observations ($\hat{y}_{it}(0)$). The estimated treatment effect (i.e., window dressing) is the weighted average of the difference between observed and imputed performance after fundraising:

$$\hat{\tau} = \sum w_{it}(y_{it} - \hat{y}_{it}(0)), \tag{1}$$

where w_{it} reflects our choice of weights. For our main results, we report a simple average of imputed treatment effects; however, other weighting choices, such as percent called or fund size, do not materially alter our results. The use of calendar time fixed effects is especially important because the 2008-2009 financial crisis (among other macroeconomic events) overlaps with the post-fundraising period for many funds in our sample. The use of fund fixed effects alleviates "apples to oranges" comparisons that arise if fund managers hold different assets, take on differential leverage, and follow different strategies.

We include one quarter lags of the fund's Brown et al. (2019) interim Public Market Equivalents (PMEs) and fund Net Asset Values (NAVs) to control for time-varying returns to scale and benchmark adjusted cash flows that LPs may also consider; however, our results are robust to other reasonable controls and to no controls. We cluster standard errors at the fund level, allowing errors to be serially correlated within funds.[18]

3.1 Identifying Assumptions

In equation (1), $\hat{\tau}$ can be interpreted as the differential change in y_{it}, primarily IRRs, for successful fundraisers relative to not-yet and never successful fundraisers. The identifying assumption is parallel trends: reported within-fund IRRs, conditional on calendar time and lagged performance controls, would follow the same trend but for whether GPs have raised

[18]Because fixed effect coefficients are calculated only in quarters where a fund has not called capital for a follow-on fund, the average within-fund residual is zero in the pre-fundraising period only, which reduces the likelihood that we overstate any post-fundraising performance declines should IRRs be mean-reverting. Accordingly, pre-trend coefficients are estimated following Borusyak et al. (2021) by regressing IRRs on event-time indicators that are accompanied by the full model of fixed effects and controls in the control sample of fund-quarter cells where the GP has not yet or never called capital for a follow-on fund.

capital for a follow-on fund in a particular quarter. Although we verify that there are no pre-trends in IRRs before GPs raise a follow-on fund, there are three endogeneity concerns to address.

First, GPs are commonly assumed to have some discretion in fundraise timing, potentially limiting the validity of our event study design. We address this concern by highlighting contractual provisions that restrict GP discretion in fundraise timing and explain PERE fundraising patterns. Although attempts to raise successor funds are clearly endogenous to the GP, these provisions ensure the timing of future fundraisings are pre-determined (or at least rationally anticipated) when the current fund closes. As a result, managers have a plausibly exogenous target window to raise a follow-on fund and thus the capacity to inflate IRRs during fundraising.

Specifically, LPAs include binding "successor fund provisions" that typically require 2-5 years to elapse before GPs can raise a follow-on fund.[19] Table A1 provides examples of the language typically seen in LPAs that restricts when managers can raise successor funds.[20] There are also prevailing industry norms around successor fund provisions that prevent much deviation: the average time between fund inceptions has been 2-5 years since 1990. Raising a follow-on fund any earlier is prohibited but might be preferred by a rational GP attempting to maximize fee income.

Given a rationally anticipated target fundraising window, we argue that GPs make asset acquisition and disposition decisions, as well as decisions to delay performance fees or inflate NAVs, to maximize reported IRRs when raising capital for a follow-on fund. Raw fundraising patterns conform closely to the terms in standard successor fund restrictions, supporting our identification. Figure A2 shows that 65% of funds in our sample that ul-

[19]These provisions are also referred to as "exclusivity" provisions. The goal of these provisions is likely to stop the GP from diverting effort or deals to new funds that favor new LPs of the successor fund at the expense of incumbent LPs of the predecessor fund. Although we cannot view the LPAs of funds in our sample directly, successor fund provisions are boilerplate in most LPAs. In a recent survey conducted by MJ Hudson, 84% of LPs report their LPAs prohibit fundraising until after (a) the investment period, (b) a fixed number of years has elapsed, or (c) once a GP deploys sufficient capital, often 70-75% of committed capital (see https://bit.ly/3bHxCSd). Additionally, a small sample of LPAs we are able to view and several PERE GPs we talked to confirm this feature is commonplace.

[20]LPs can negotiate separate side letters modifying the LPA. However, successor fund provisions are rarely specific to a particular LP and hence are rarely modified by side letters. de Fontenay and Nili (2022) report that only 1.6% of side letters they analyzed alter restrictions on successor fund formation.

timately raise a follow-on fund (by the Brown et al. (2019) definition) do so within 3-5 years and 31% do so in year 5 alone. Further, fund and calendar time fixed effects in our DiD specification eliminate the effects of common time varying fundraising conditions and GP-specific bargaining power over LPA terms.

A second concern is that causality might flow in reverse; variation in reported IRRs could determine fundraise timing. Barber and Yasuda (2017) conclude that peak performance often coincides with fundraising events. However, we argue that reverse causality is limited in our context. For it to explain our results, interim IRRs must exogenously peak within the typical fundraising window, inducing managers to raise follow-on funds. In our internet appendix, we show fundraising events coincide with proportionally higher distributions by the GPs and not with higher market returns. These results make it challenging to interpret the average fundraise timing as an innocuous response to unexpected and favorable market conditions. Moreover, reverse causality seems implausible since the pattern of performance peaks during anticipated fundraising events holds across our study of 51 unique fundraising cohorts spread across 13 years.

Lastly, changes in time-varying omitted factors might coincide with fundraising events (potentially causing both fundraising success and shifts in performance). To address this concern, we show that our treatment effect estimates are attributable to window dressing-like behavior identified in previous literature (e.g., grandstanding). Hence, for any time-varying omitted factor to cause changes in IRRs around fundraising, GPs that exhibit behavior consistent with window dressing techniques from previous studies must also load on this omitted factor. We describe manipulation techniques in section 4.2.1, and Table A2 provides a summary.

4 Main Results

4.1 Effect of Fundraising on Reported Performance

Table 3 reports the average effect of raising a follow-on fund on IRR from our DiD regressions described in section 3. We additionally report the average effects of raising a follow-on fund on widely used performance metrics, TVPI and PME. Columns (4) and (5) decompose the TVPI result into DPI and RVPI. These components respectively show how the value of realized and unrealized distributions to LPs change around fundraising. We include fund and year-quarter fixed effects alongside lagged PMEs and NAVs as controls. Standard errors are clustered at the fund level.

Panel A indicates that net-of-fee IRRs decline by 470 basis points after fundraising. The IRR decline is both statistically significant and economically meaningful; 470 bps equals roughly half of the median to-date IRR reported during fundraising and is close to the average final IRR of 5.45% in our sample. Panel A also shows that TVPI and PME are unaffected by fundraising for a follow-on fund.[21] This difference between IRR and alternative performance metrics likely arises because IRR is relatively more susceptible to cash-flow timing manipulations (Phalippou 2008). Columns (4) and (5) show that distributions to LPs increase more so than the value of unexited investments decrease after fundraising.

Panel B presents the results of falsification tests using the same fixed effects and controls as the regressions reported in Panel A. To ensure we are not picking up a spurious relation driven by cyclical factors or other unobservables not easily captured by fund or calendar time fixed effects, we randomize fundraising outcomes and timings, then recalculate the same results. Panel B shows mostly positive IRR coefficients that are either significant at the 10% level or insignificant across all falsification specifications. The same pattern is not present for TVPI and PME. This ensures that the fundraise timing and outcomes for GPs featured in our data are needed to produce our IRR findings. More generally, this supports our results on the sign, timing, and size of the effect. In our internet appendix, we further subject our results to a battery of robustness tests involving different specifications, DiD estimators, and data sources (Preqin) to confirm our results do not depend on the precise way in which we conduct our analysis.

Figure 3 plots the dynamic difference-in-differences estimate of the effect of fundrais-

[21] To clarify the interpretation of our results, the IRR estimate indicates that, on average, the post-fundraising to-date IRR is 470 bps lower than a counterfactual constructed using pre-fundraising observations. For example, if the counterfactual post-fundraising IRR is 10% based on pre-fundraising observations, this estimate implies that the average to-date IRR is 5.3% after calling capital for a follow-on fund. Analogously, the TVPI and PME estimates indicate that post-fundraising counterfactuals constructed using pre-fundraising observations are respectively 0.066 and 0.026 lower than the post-fundraising observed to-date TVPI and PME.

ing on reported IRRs around the fundraising quarter. The event-study plot shows no pre-trends and a clear monotonic decline in reported IRRs post-fundraising, consistent with our parallel trends identifying assumption.[22]

Overall, these results show IRR declines after fundraising are an economically meaningful feature of PERE performance reporting. By definition, our treatment effects only apply to funds where the GP raised a follow-on fund. Despite large reported performance declines consistent with IRR manipulations, 93% of funds in our sample successfully raised follow-on funds. Regardless of the performance declines, investors still tend to commit capital to subsequent funds. To further ensure we can interpret IRR declines as manipulations and to dissect this result further, we next examine possible explanations for how IRRs come to be inflated during fundraising quarters.

4.2 Attribution Analysis

In this section, we examine what tangible actions, if any, GPs may take to boost reported IRRs before and during fundraising for a follow-on fund. We first collate several techniques from previous literature to create a manipulation "playbook." We then test the relative ability of each manipulation technique to explain our results.

4.2.1 IRR Manipulation Techniques

We focus on two major, and non-mutually exclusive, groupings of manipulation techniques: valuation and timing based. For the former, interim to-date performance metrics are calculated using non-traded and illiquid holdings, which affords the GP discretion in reported valuations.[23] For the latter, GPs can boost returns by strategically timing calls, distributions, mark-downs, and fee-related expenses. Korteweg and Westerfield (2022) survey PE return manipulation methods in the context of LP asset allocations.

The first manipulation technique we consider involves "quick flip" investments. GPs might manipulate dollar-weighted IRRs by exiting better-performing investments earlier

[22]Our pre-trend plot only includes one year before treatment because earlier IRRs tend to be less meaningful and disregarded by LPs.

[23]GPs typically hire an independent appraiser to value underlying properties once every one to two years. GPs are then responsible for interim valuation adjustments, if any.

and holding underperforming assets longer, effectively "selling winners and holding losers." Phalippou (2008) provides evidence consistent with GPs selling winners early. Lopez-de-Silanes et al. (2015) provide evidence consistent with GPs holding losers. A key friction is whether asset disposals are strategically timed such that IRRs peak during fundraising. A fund is said to have strategically engaged in quick flips if (1) its DPI per year at the time of the fundraising quarter is in the top tercile of all DPIs per year during fundraising quarters (measured in event time) and (2) once $RVPI_{it} < .05$ and the fund is close to liquidated with few remaining unexited investments.[24] The first condition captures whether GPs sell winners before raising capital for a follow-on fund. The second condition tests whether GPs hold their "losers," i.e., whether IRR declines are driven by any underperformance of assets that remain in the fund towards the end of its life.

GPs might also manipulate IRRs by waiting to mark-down underperforming investments until after raising a follow-on fund. We measure mark-downs following Barber and Yasuda (2017) as:

$$\text{Mark-down}_{it} = \frac{\min(NAV_{it} - NAV_{i,t-1} + (Distributions_{it} - Calls_{it}), 0)}{\text{Fund Size}_i}. \tag{2}$$

Barber and Yasuda (2017) and Chakraborty and Ewens (2018) find that mark-downs tend to increase following fundraising. We consider a fund to be delaying mark-downs if the sum of its mark-downs for the year immediately following fundraising is in the top tercile of all mark-downs for the year after fundraising, measured in event time.[25]

Another manipulation technique is "grandstanding." GPs might exit their best investments, sending an inflated signal about skill, before fundraising to entice LPs to invest

[24]For example, if a GP reports a DPI of 1.2 and raises capital for a follow-on fund at quarter 16, its quick-flip value would be $1.2/16 = 0.075$. If the GP instead called capital for a follow-on fund at quarter 20, then its quick-flip value would be $1.2/20 = .06$ and we would be less likely to label this return pattern as consistent with quick flips.

[25]In strict terms, the events captured in equation (2) are unlikely to be complete write-offs, as mentioned in studies of venture funds (e.g., Barber and Yasuda (2017) and Chakraborty and Ewens (2018)). This is because CRE assets almost always have some residual value even if they produce negative property-level IRRs. Additionally, as discussed by Brown et al. (2019), this measure does not directly indicate that NAVs are overstated prior to and during fundraising as this measure may also capture confounding events such as a GP's propensity to *delay revealing* effort constraints that may bind once managing capital for the follow-on fund or weak performance in the current fund. However, all interpretations are consistent with our broader manipulation definition.

in successor funds. However, this creates a performance trend likely to collapse once the GP disposes of the fund's higher-quality holdings. Gompers (1996) shows grandstanding around fundraising is common in venture capital, especially among managers with weaker track records. We consider a GP to be grandstanding if its DPI growth the year before fundraising is in the top tercile of all DPI growths the year before fundraising, measured in event time. This technique is similar to the quick flips but is measured relative to previous DPIs rather than in fund life event time. Empirically, we find the two to be highly correlated but nonetheless consider each technique separately.[26]

A novel technique we consider is performance fee timing. One such manipulable fee is carried interest—a GP's senior claim to a fraction of all earnings that exceed a hurdle rate (also called performance fees—often 20% with an 8% hurdle).[27] Because the LP's IRR net of carried interest is less than the LP's IRR gross of carried interest, GPs might strategically defer asset sales or otherwise avoid triggering carried interest receipt until after they raise a follow-on fund to avoid lowering net IRRs.[28] A GP is said to be deferring performance fees if the fund is eligible to receive carried interest based on its performance but has yet to make the requisite distributions to LPs to trigger carried interest for a rolling four quarters. Specifically, we define "Carry" in a given fund-quarter cell as:

$$\mathbb{1}\{\text{Carry}\}_{it} = \begin{cases} 1, & \text{if } \left(\frac{1}{4}\sum_{t-4}^{t} TVPI_{it}\right) \geq 1 + \text{hurdle}_i \text{ and } DPI_{it} < 1 + \text{hurdle}_i \\ 0, & \text{otherwise} \end{cases}. \tag{3}$$

Should the GPs that are "deferring" carried interest exit property investments at current valuations, they would receive carried interest, but these GPs have not yet made the requisite

[26]For example, if a GP reports a DPI of 1.2 during the fundraising quarter and a DPI of 0.8 one year prior, its grandstanding value would be $1.2/0.8 - 1 = 50\%$. If the GP instead reported DPI of 1.1 one year prior, its grandstanding value would be 9.1% and we would be less likely to label this pattern as consistent with grandstanding. The quick flips value, in contrast, is not measured relative to the previous DPI but rather relative to the number of quarters elapsed. The GP could raise a follow-on fund in quarter 30, implying a low quick flips value, but still be grandstanding if the DPI growth is sufficiently high.

[27]Metrick and Yasuda (2010) discuss fees paid to PE managers more generally. We assume that funds use "Whole-Fund" carry provisions, whereby GPs are entitled to carried interest once the realized return for the whole fund exceeds the hurdle rate, which is typical for PERE funds. Our results are robust to more complicated carry calculations that compound the hurdle rate of return.

[28]It is not obvious ex-ante whether doing so is attractive to GPs as the receipt of carried interest may also signal skill. Moreover, there could be measurement error if funds deduct carried interest from gross IRRs on an accrual basis.

sales. The rolling four quarters help to mitigate potential frictions in asset disposal. We assume the hurdle rate is 8% unless stated otherwise in Preqin. The average fund with at least 40 quarters of IRR data defers carried interest for about 20% of its life, however there is significant variation with a standard deviation of about 20%.

Delaying carried interest is negatively correlated with grandstanding and quick-flips strategies and can work in the opposite direction as it involves deferring, rather than expediting, distributions to LPs. This technique suggests that certain PERE GPs tradeoff between carried interest receipt and raising a follow-on fund. This technique complements, but is distinct from, work by Robinson and Sensoy (2013) who show that some buyout and venture managers accelerate distributions to LPs around the first date carried interest can be awarded (the "waterfall date").

Lastly, GPs might manipulate IRRs by overstating or aggressively marking up the estimated values of illiquid portfolio investments around fundraising. We measure overstated NAVs following the robust identification of excess returns to NAVs introduced in Brown et al. (2019) as:

$$NAVbias_{it} = \log(NAV_{it}) - \log(NAV_{it} \times R_{it} + (Distributions_{it} - Calls_{it})). \tag{4}$$

R_{it} is the quarterly gross return from the Nareit real estate benchmark. Brown et al. (2019) show that buyout and venture funds do not overstate NAVs on average, but GPs that fail to raise follow-on funds often do. We consider a fund to be overstating NAVs if the average $NAVbias$ in the year before fundraising is in the top tercile of all average $NAVbias$ observations for the year before fundraising, measured in event time. Table A2 provides a summary of the window dressing techniques we evaluate.

4.2.2 Return Manipulation Channels

With a "playbook" for manipulating IRRs in hand, we turn to the data to examine which techniques are most important. Table 4 presents evidence on the extent to which the effect of fundraising on net-of-fee IRRs presented in Table 3 is attributable to window dressing-like behavior identified in previous literature. We remove funds that exhibit key features of several manipulation techniques and recalculate the effect of fundraising on reported IRRs within the resulting sub-samples. We include fund and year-quarter fixed effects and lagged interim PME and NAV as controls. Standard errors are clustered at the fund level.

Panel A displays the results obtained after removing funds with performance reporting patterns consistent with each window dressing technique. Panel B contains the results obtained after removing funds with performance reporting patterns consistent with window dressing techniques cumulatively. The resulting sub-samples retain all unsuccessful fundraisers to moderate bias from the limited never-treated observations in later calendar-time cells. Figure 4 provides a visual summary of the variation in the treatment effects after implementing this procedure.

Panel A of Table 4 shows that the effect of fundraising on IRR attenuates from −470 bps to −280 bps after removing funds that exhibit behavior consistent with quick flips and to −330 bps after removing funds that appear to delay NAV mark-downs until after fundraising. Removing funds that engaged in grandstanding results in an effect of −420 bps rather than −470 bps. This limited attenuation suggests the "holding losers" aspect of quick flips has the strongest impact on fund IRR declines. The attenuation associated with grandstanding is also comparable to that produced after accounting for our novel channel of delaying carried interest and the NAV manipulation channel. Panel B shows that IRRs decline after fundraising by an insignificant 110 basis points after accounting for the quick flips, markdown delay, carry deferrment, and grandstanding channels (column (4)). However, the NAV misstatement channel fails to further attenuate the effect of fundraising on IRRs.[29]

A common feature of the window dressing techniques that explain most of the IRR decline is that they do not rely on explicit misstatements of ongoing asset values. In contrast, GPs rely primarily on timing manipulations: several timing manipulations account for approximately 75% ($\approx (470-110)/470$) of the performance decline. These results are consistent with a series of window dressing techniques proposed by Phalippou (2008), Lopez-de-Silanes

[29] In our internet appendix, we examine the role of FASB 157 Topic ASC 820, which requires funds to value assets at fair value every quarter, rather at cost, effective in 2009. Brown et al. (2019) provide evidence that this accounting change improved interim markings for venture funds but not for buyout funds. We find similar treatment effects in sub-samples split before and after the 2009 vintage, but do not further interpret the results given compositional differences among GPs that raised capital for subsequent funds during the financial crisis.

et al. (2015), Barber and Yasuda (2017), and Chakraborty and Ewens (2018). These results also complement recent work by Brown et al. (2019) and Hüther (2021) in buyout and venture funds.[30]

More generally, these findings also support our interpretation of the post-fundraising decline as return manipulation. There is strong evidence of window dressing on average, but not in the sub-sample of funds that do not exhibit window-dressing behavior. For any omitted factor to be the main driver of IRR changes around fundraising, it must also be true that funds that exhibit behavior consistent with window dressing from previous studies also load on this omitted factor.

4.3 IRR Manipulations and Investor Performance Sensitivity

In this section, we examine our catering view of return manipulation. To do so, we analyze whether cross-sectional variation in investor fund allocations explains IRR manipulations. We define *Investor Performance Sensitivity* for fund i as the average of each LP's commitment to the fund (c_{ij}) scaled by the LP's total Assets Under Management (AUM) retrieved from Preqin in February 2022:

$$\text{Investor Performance Sensitivity}_i = \frac{1}{J} \sum_{j \leq J} \frac{c_{ij}}{AUM_j}. \tag{5}$$

Equation (5) determines the elasticity of investor benefits from higher interim fund returns and is in the spirit of Bergstresser et al. (2006). Our measure captures whether one fund is on average more important for the portfolio level returns of its LPs than another. Naturally, our measure is positively related to return manipulations if GPs cater to their LPs. Accordingly, our tests assess whether cross-sectional variation in the elasticity of investor benefits predicts whether GPs ultimately boost IRRs.[31]

[30] In untabulated results, we further confirm that excess returns to NAV– the Brown et al. (2019) measure of NAV bias– are persistently negative throughout the fund's life and seemingly unaffected by anticipated fundraising events. These patterns are present among both successful and unsuccessful fundraisers and suggest GPs are conservative with their NAV markings, on average.

[31] The limitations of this measure are that the AUM values are present-day biased and that commitments are estimated rather than observed for a large portion of investors. Nonetheless, both limitations appear to be inconsequential for our main results. Our findings are qualitatively unchanged if we focus on the sub-samples of funds less affected by these limitations where LP commitment values are not imputed or

To illustrate, consider the potential incentives of two PERE GPs after receiving LP capital commitments that produce different performance sensitivities. In 2012, Kansas City Public School Retirement System (KCPSRS) committed \$25 million to a Brookfield fund, equal to 3.6% of KCPSRS's 2022 AUM. Conversely, the Alaska Permanent Fund Corporation (APFC) committed \$25 million to a Blackstone fund in 2011, equivalent to .03% of APFC's 2022 AUM. If Brookfield boosts IRRs by 400 bps, the manipulation roughly increases portfolio level IRRs for KCPRS by 14 bps ($= 4\% \times 3.6\%$). In contrast, if Blackstone boosts IRRs by 400 bps, the same manipulation only increases portfolio level IRRs for APFC by 0.1 bps ($= 4\% \times .03\%$). In this setup, our measure suggests that KCPSRS stands to benefit more per unit of manipulation than does APFC. Our empirical strategy thus examines whether such variation in the average return elasticity of LP investors means the GPs of the Brookfield fund are more likely to manipulate interim IRRs than the GPs of the Blackstone fund.

Because fund fixed effects absorb the heterogeneity of investor return sensitivities in our main specification, we assign funds to "high" and "low" investor performance sensitivity groups based on whether equation (5) for a given fund is above or below the median investor performance sensitivity for all funds. We keep all unsuccessful fundraisers (never-treated funds) in each sub-sample. We then recalculate the effect of fundraising on reported IRRs following section 3 within each sub-sample.

We present our results in Table 5. Columns (1) and (2) show that IRR manipulations average 640 bps for funds with investors contributing above median shares of their total AUM. In contrast, we estimate that IRR manipulations average an insignificant 110 bps among funds in which investors contribute a below median share of their total AUM to the fund. Thus, GPs are more aggressive with IRR manipulations when fund performance has a greater impact on LP total returns.

Although an LP's allocation to a single fund usually cannot comprise a large portion of the LP's assets, we estimate that these manipulations nonetheless distort LP-level IRRs. The median investor in a "high" sensitivity fund allocates 3.69% of its AUM to the fund,

where historical, rather than present-day, LP AUM are known. Our results are also robust to permutations of equation (5), such as value-weighting and medians, further suggesting the core economic message of our measure is not contaminated by spurious data concerns. Moreover, in our internet appendix we show that our results are similar if we instead scale the commitment to each fund by rolling averages of the LP's previous commitments to other private funds, rather than by AUM, before averaging at the fund level.

while the median investor in "low" sensitivity fund allocates 0.11% of its assets to the fund. Manipulations thus add about 24 basis points of IRR (= 6.4% × 3.69%) for the average investor in high-elasticity funds. In contrast, manipulations only add about 0.1 basis points of annualized returns (= 1.1% × 0.11%) for investors in low-elasticity funds.

In the remaining columns of Table 5, we repeat the analysis with permutations of equation (5). Specifically, we recalculate investor sensitivities, using only the AUM allocated to (1) alternative assets, (2) real estate assets, and (3) private real estate assets respectively. These data are also provided by Preqin. For real estate asset allocations, Preqin provides target real estate allocations rather than actual real estate allocations. The additional sensitivity measures are positively correlated with one another but attain different distributional properties. The results presented in columns (3)-(8) show the main results in columns (1) and (2) hold across alternate measures of performance sensitivity that account for LP participation in increasingly narrow asset classes.

Figure 5 plots the dynamic difference-in-differences estimates of the effect of fundraising on reported IRR around the fundraising quarter within each sub-sample of high and low investor performance elasticities. Panel A displays results when investor sensitivity is calculated using the total AUM and the remaining panels display results for performance sensitivities calculated using more narrowly defined AUM. Across each measure of investor performance sensitivity, the event-study plot shows no pre-trends, consistent with our parallel trends identifying assumption within each sub-sample. The above-median performance sensitivity groups display a clear monotonic decline in reported IRRs post-fundraising, whereas the below-median groups show moderate or no declines in IRRs after fundraising. Overall, these results show that investor performance sensitivity is an important determinant of GP return manipulations.

Two features of our data make it unlikely that investors disapprove of manipulations. First, 93% of funds in our sample successfully raised follow-on funds. Second, larger, rather than smaller, allocations predict IRR manipulations. If investors punish IRR manipulations, we would instead expect a negative link between LP allocations and manipulation propensity. These results are therefore consistent with the view that some PE fund managers manipulate interim returns in a manner consistent with their investors' desires. Return manipulation tends to be incentive compatible for PERE GPs if the relative benefits to investors, in the form of increased interim returns, are higher.

4.3.1 Determinants of Allocations

We next examine an agency-based explanation for why PERE GPs tend to manipulate interim returns if they manage a larger share of their investors' assets. Specifically, we link agency frictions within investor organizations to proportional allocations to a given fund in our sample of U.S. defined benefit public pension fund LPs. The data are more readily available for these investors and there is a large literature outlining agency conflicts in public pension plan investment structures (e.g., Romano (1993)).

We consider two specific agency costs. First, we examine what Dyck et al. (2021) call "outrage risk": the reluctance of many public pension boards to compensate their Chief Investment Officers (CIOs) at market rates because doing so might upset their plan beneficiaries. In equilibrium, agency costs from "outrage risk" are thus highest among pension plans that pay their investment managers relatively less.

Second, we examine the findings of Andonov et al. (2017) who show that lower funding ratios can induce boards to "risk up" their portfolios to improve their funding ratios. Dyck et al. (2021) suggest that an agency-based mechanism is at play: pension managers prefer to increase their funding ratios through risky asset exposure rather than disclose funding shortfalls to legislatures. If boards allocate more to riskier asset classes, including PERE, their expected asset return increases. According to U.S. regulations, this lowers the present value of pension liabilities (i.e., obligations to pension beneficiaries) and helps improve the funding status of the pension plan.[32]

Our novel combination of PPD data and Preqin commitments enables us to test whether stronger evidence of outrage risk (i.e., lower salaries among CIOs) or stronger incentives to risk-up (i.e., worse funding statuses) predict higher allocations to PERE funds. We regress the commitments made by each public pension plan to each PERE fund on the pension's funding ratio, the log ratio of CIO pay to the average salary of working pension

[32]Novy-Marx and Rauh (2011) show that this regulation clearly overstates funding ratios.

beneficiaries, and the log of CIO pay during the commitment year.[33] We scale commitments to PERE funds by pension plan assets, consistent with our primary measure of investor performance elasticity. We include year fixed effects to account for time trends in compensation levels and pension funding. We additionally include the total pension returns in the previous year and the CIO tenure as of the commitment as controls. Standard errors are clustered at the pension level.

The results displayed in Table 6 show that proportional allocations to a given PERE fund are negatively related to funding ratios and CIO pay. All estimated coefficients are statistically significant at the 1% level. Column (1) shows that a one standard deviation decrease in the funding ratio (equal to 0.16) translates to an incremental 0.05% of total assets allocated to a given PERE fund. Column (2) shows that a one standard deviation decrease in the ratio of CIO pay to pensioner salary (equal to 0.54) translates to an incremental 0.06% allocation to a given PERE fund. Given that the median fund allocation is about 0.2% of a public pension's assets, these incremental changes are economically meaningful, equivalent to allocating to an additional PERE fund once every 3-4 years. The remaining columns show that these results are robust to simultaneously including funding ratios and CIO pay as right-hand side variables.

These results show that agency frictions within public pensions, as documented by Andonov et al. (2017) and Dyck et al. (2021), are related to an important determinant of GP return manipulation decisions: individual investor performance sensitivities. Taken together, these findings suggest the traditional view that return manipulation is punished or disliked by LPs does not capture the full complexity of the manipulation decision for GPs. This finding is consistent with a mechanism by which agency frictions within LP organizations incentivize some LP investment managers to allocate a larger share of their assets to opaque PERE funds to attain smooth and boosted interim returns.

[33]To better ensure that we accurately capture average allocations, we exclude one outlier commitment that exceeds 10% of a pension plan's assets. Although our results are robust to including this observation, the next highest allocation in our sample with CIO salary data is 2% of a plan's assets and only 3 out of 1,076 commitments to PERE funds exceed 2% of plan assets.

4.4 Heterogeneity Analysis and Alternative Explanations

In this section, we consider additional sources of heterogeneity in IRR manipulation incentives and assess their relation to window dressing outcomes. We then examine whether they moderate the positive relationship between IRR manipulations and investor performance sensitivity.

Similar to previous tests, we assign funds to "high" and "low" sub-samples based on fund or investor characteristics. For continuous characteristics, these sub-samples respectively indicate whether the characteristic for a given fund is above or below the median characteristic for all funds. We keep all unsuccessful fundraisers (never-treated funds) in each sub-sample. We then recalculate the effect of fundraising on reported IRRs within each sub-sample. We include fund and year-quarter fixed effects and lagged interim PMEs and NAV. We present these results in Table 7 and discuss each result in detail in the following subsections. Section 4.4.1 focuses on the relation between IRR manipulations and investor characteristics. Section 4.4.2 focuses on the relation between IRR manipulations and fund characteristics.

4.4.1 Investor Characteristics

We start by examining the relation between investor sophistication and window dressing. A large literature demonstrates that LPs have heterogeneous investment skills (e.g., Lerner, Schoar, and Wongsunwai (2007), Sensoy, Wang, and Weisbach (2014), and Cavagnaro, Sensoy, Wang, and Weisbach (2019)). Accordingly, an important, yet distinct, question is whether LPs heterogeneously detect return manipulation. It is possible that some of the funds in our sample were consistently able to mislead their investors and manipulate returns undetected. If so, we would expect GPs to window dress more in funds with less sophisticated LPs. We construct three separate measures of investor sophistication.

First, we proxy for LP skill by the average realized performance of a LP's investments made before the time of commitment (measured using TVPI), in parallel to Phalippou, Rauch, and Umber (2018) and Cavagnaro et al. (2019). We measure LP performance using only PERE investments because LPs often have separate investing experiences and histories for each asset class. Second, we proxy for LP familiarity with a fund sponsor using the cumulative number of commitments a LP made to a given GP before the time of the current commitment. Third, we proxy for LP familiarity with PERE as the number of previous PERE investments a LP has made. We scale this number by the average number of cumulative PERE investments per LP at the time of commitment to better capture relative experience and avoid under-weighting earlier commitments. To conduct our DiD analysis, we average each measure at the fund level. These measures are only weakly correlated with one another, suggesting they capture different aspects of fund LPs.

Panel A of Table 7 shows that GPs tend to manipulate IRRs if their LPs have generally invested in high performing PERE funds or if their LPs have made more investments in their previous funds. We estimate that IRR manipulations average 520 bps among funds whose investors have above-median past performance but an insignificant 210 bps among funds whose investors have below-median past performance. Similarly, the average IRR manipulation is 500 bps for funds whose investors made an above-median number of commitments to the same GP. The corresponding average manipulation is an insignificant 250 bps for funds whose investors have made a below-median number of commitments to the same GP. The remaining two columns show that the number of previous PERE investments made by investors appears to be only weakly related to the observed window dressing.

Overall, these results suggest return manipulations are not confined to funds with less sophisticated LPs who are less likely to detect manipulations. If anything, return manipulations occur more frequently among funds with arguably more sophisticated investors – as measured by past performance and familiarity with the fund's GP. Importantly, the presence of window dressing among funds that have more, rather than fewer, returning LPs is consistent with some investors exhibiting a desire for overstated or otherwise boosted interim returns.

4.4.2 Fund Characteristics

Next, we examine whether fund characteristics influence IRR manipulations. GPs might inflate interim IRRs to match differential LP expectations about their final returns due to their reputation (Barber and Yasuda 2017) or underlying asset risk. LPs might also be less likely to monitor GPs if the LPs are sufficiently dispersed, in the spirit of Shleifer and Vishny (1986). We therefore extend our analysis by considering three sets of fund characteristics:

- *Reputation*: a fund belongs to a "high-reputation" GP if the GP has at least three predecessor funds and has raised more than $1.5 billion in cumulative capital before the current fund was brought to market. Otherwise it was offered by a "low-reputation" GP, similar to the definition employed by Barber and Yasuda (2017).

- *Fund HHI*: a fund has "concentrated" investors if the fund's HHI of commitments is above the sample median and a "dispersed" investor base otherwise.

- *Fund Risk*: a fund is "high-risk" if it pursues an opportunistic or distress investment strategy. In contrast, we consider funds to be relatively "low-risk" if they pursue a core, core-plus, or value-added strategy.

These fund characteristics are weakly and negatively correlated with one another. The results presented in Panel B of Table 7 shows GPs tend to window dress if they have dispersed investors, or manage high-risk funds (columns (3) - (6)). We estimate that IRR manipulations average 450 bps for funds with below-median HHIs but only 250 bps for funds with above-median HHIs. Additionally, we estimate that IRR manipulations equal 520 bps for high risk funds but only 220 bps for low-risk funds. There is also evidence of window dressing among both low and high-reputation managers. IRR manipulations average 490 bps for funds with low reputation GPs and 370 bps for funds with high-reputation GPs.

The evidence presented in Panel B of Table 7 suggests that GPs of certain types of funds are more likely to manipulate returns. None of these results are inconsistent with a relationship between investor performance sensitivity and window dressing behavior. These results instead add depth to the types of GPs that are more likely to produce manipulated interim returns. Importantly, the role of reputation has little to no moderating effect, consistent with Brown et al. (2019), and instead suggests manipulation decisions are largely determined by conditions and characteristics of the current fund, not necessarily based on the GP's previous fundraising record.[34] In fact, our previous results related to investor per-

[34]In untabulated results, we find little to no evidence of manipulation persistence in our sample on both the intensive and extensive margins.

formance sensitivity suggest one of the most important characteristics of the current fund is the type of LPs it has attracted and whether it is relatively more beneficial for managers to ensure their investors receive high interim returns.

4.4.3 Alternative Explanations

Previously documented cross-sectional variation in performance sensitivity might proxy for an omitted variable that influences the GP's manipulation decision. To address this concern, we examine whether any of the cross-sectional variation in window dressing due to fund or investor characteristics (sections 4.4.1 and 4.4.2) explains the positive relationship between investor performance sensitivity and IRR manipulations.

We first assign funds to "high" and "low" investor performance sensitivity groups based on whether the estimated performance sensitivity from equation (5) for a given fund is above or below the median investor sensitivity for all funds. We then further assign funds to sub-samples based on the investor characteristics considered in Section 4.4.1 and fund characteristics considered in Section 4.4.2. Each fund retains its classifications from previous tests but with an overlayed additional classification. Previously discussed fund and investor characteristics are mostly uncorrelated with investor performance sensitivity scores. We keep all unsuccessful fundraisers (never-treated funds) in each sub-sample. We then recalculate the effect of fundraising on reported IRRs following section 3. Tables 8 and 9 present the results of this exercise.

Although Table 7 shows measures of investor sophistication generate some cross-sectional variation in window dressing, the results presented in Table 8 show this variation is conditional on investor performance sensitivity. The results displayed in columns (1) and (2) show that IRR manipulations are economically and statistically significant for all sub-samples with "high" performance sensitivity investors. However, estimates of IRR manipulations are not significant among the funds with "low" performance-sensitivity investors. The remaining columns of Table 8 present estimates of IRR manipulations using additional permutations of our performance sensitivity measure. These columns confirm the finding that statistically significant and economically large window dressing is concentrated among funds with high performance sensitivity investors within narrow subsets of AUM allocated to; alternative assets, real estate, and private real estate.

Table 9 shows evidence that IRR manipulations occur almost exclusively among funds with above median performance sensitivity investors after conditioning on other fund characteristics. The results presented in column (1) show that IRR manipulations are negative and statistically significant at the 1% level among sub-samples with "high" performance sensitivity investors. In contrast, the results presented in column (2) show no evidence of statistically significant IRR manipulations for sub-samples with "low" performance sensitivity investors.

Although fund risk and fund HHI appear to independently predict window dressing in Table 7, these characteristics fail to predict window dressing after accounting for investor performance sensitivity. For instance, there is strong evidence of window dressing among high risk funds (620 bps) and none for low risk funds (220 bps); however, this effect is exclusive to funds that have high performance sensitivity investors.

The remaining columns in Table 9 show these results are generally true for alternate measures of performance sensitivity that account for the LP idiosyncratic participation in the increasingly narrow asset classes of alternative assets, real estate, and private real estate. With the exception of the low-risk fund cross-section, the post fundraising IRR decline is negative and statistically significant for all sub-samples of fund characteristics with "high" performance sensitivity investors but not for funds with "low" performance-sensitivity investors.

Overall, these results show our catering proposition is distinct from several alternative mechanisms. Additional cross-sections fail to moderate the relationship between IRR manipulations and investor performance sensitivity. In contrast, these results provide further support for the conclusion that IRR manipulations by GPs are driven by an LP "appetite" for manipulated interim returns.

5 Conclusion

The central message of our paper is that some PERE GPs manipulate interim returns in a manner consistent with their investors' desire for such boosted returns. PERE GPs do not appear to manipulate interim returns to fool their LPs, but rather because their LPs want them to do so. This allows these LPs to report higher returns alongside lower reported volatility in the short term. This catering view of return manipulation is consistent with the overwhelming LP preference to access real estate investments through PERE funds rather than more volatile marked-to-market REITs.

In our difference-in-differences analysis, we exploit staggered fundraising event timing and institutional features of PE fundraising to measure interim IRR manipulations. We show manipulations are widespread, economically significant (amounting to about 470 bps), and accomplished primarily through a diverse set of timing strategies. The prevalence of timing strategies, rather than explicit NAV manipulations, suggests that only some forms of manipulation are acceptable to LPs.

We then relate return manipulations to LP return elasticities, as measured by the average effect of a PERE fund's returns on its LPs' portfolio returns. We find that cross-sectional variation in LP return elasticities strongly predicts GP return manipulations. These manipulations result in noticeable boosts of about 24 bps annually to reported LP-level IRRs for the average performance-sensitive LP.

We find markedly little evidence that IRR manipulations hurt GP attempts at raising capital for follow-on funds. In fact, the average GP that manipulates IRRs successfully raises capital for a follow-on fund and manages larger commitments from their LPs. Additional cross-sectional analysis shows that our results are inconsistent with models in which investors punish or are otherwise deceived by manipulations. Measures of investor sophistication, GP reputation, and investor monitoring incentives have little ability to explain the intensity of return manipulations after accounting for investor return elasticity. In other words, our results indicate that PERE return manipulation is demand-driven.

We offer and provide empirical support for a simple explanation of this catering phenomenon: some PE investors face agency costs within their organizations that make manipulated interim returns attractive. Individual investment managers within LP organizations often face shorter investment horizons than their principals (such as tax payers and pension beneficiaries) and may stand to benefit from boosted and smoothed short-term returns. Previous studies indicate that, in equilibrium, agency frictions are high among U.S. public pension funds that are underfunded or that pay their CIOs relatively less. The mechanisms at play center on pension trustee aversion to disclosing funding shortfalls to state legislatures and upsetting plan beneficiaries (e.g., Dyck et al. (2021)).

We link annual reports by U.S. public pensions with our primary measure of LP return sensitivity at the LP level. Consistent with an agency explanation, we find that underfunded pensions are more likely to allocate a higher fraction of their assets to a given PERE fund. Similarly, public pension CIO compensation is negatively related to the proportion of pension assets allocated to a given PERE fund. These results show that agency frictions within public pensions are associated with determinants of GP return manipulation decisions.

Overall, our results point to an underlying tension in PE performance: the "phony happiness" that some PE investors receive from overstated and smoothed interim returns due to agency frictions within their organizations. The extent to which this micro-level phony happiness translates to macro-level PE allocations remains an open and intriguing question. As LPs increasingly delegate capital to alternative asset managers, it is fruitful to consider constraints faced by LPs that can explain these allocations, as suggested recently by Cochrane (2022). Our catering perspective offers a promising angle insofar as the equilibrium level of return manipulation is related to the agency frictions that stimulate LP demand for manipulated returns. LP constraints are increasingly pertinent in our context of PERE funds, where there is mounting evidence that PERE funds have failed to match returns produced by alternative modes of real estate investing, underperforming by 300 - 400 bps per year.

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Figure 1: Reported Interim IRR

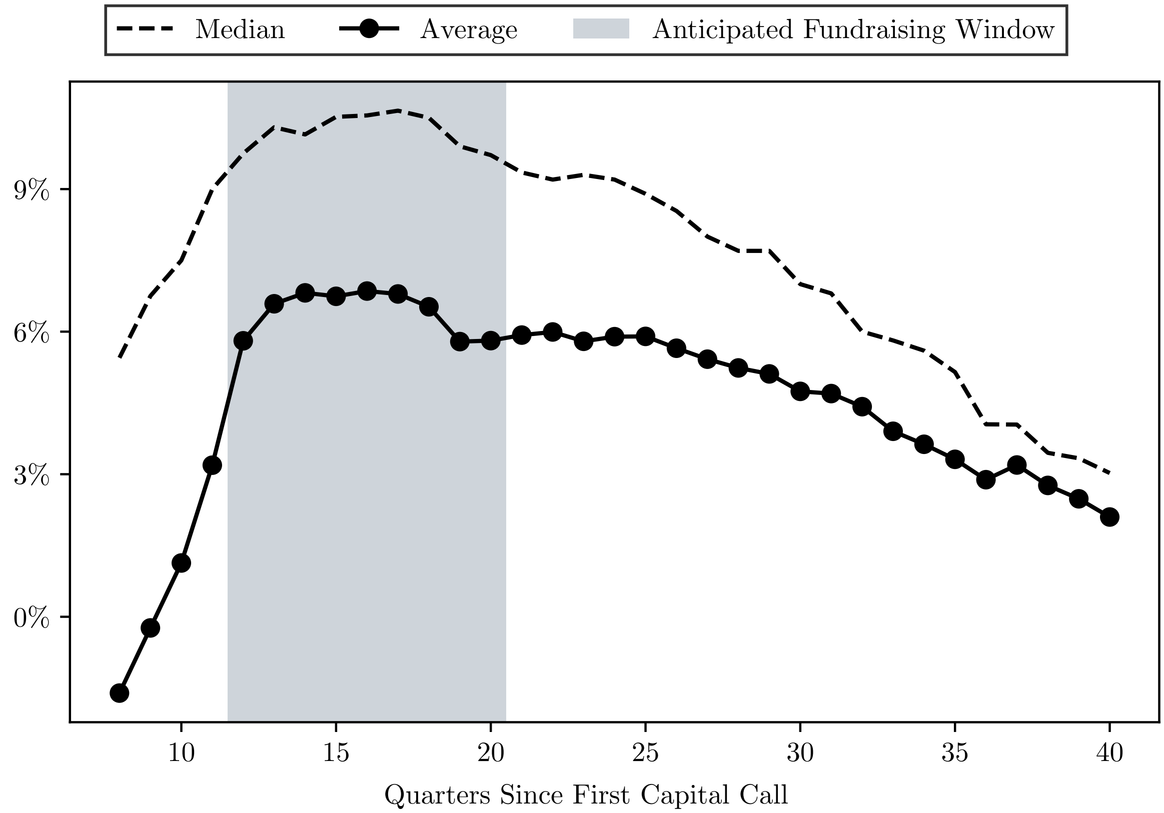

Figure 1: Plots the average and median IRRs since the first capital call for the 416 out of 448 funds in our sample of funds with vintage years 2001-2014 that successfully raised a subsequent fund. IRR reports for each fund are annualized, net-of-fees, and "to-date" measures, reflecting expected returns over the funds' lives as of a given quarter. The plot is restricted to quarters 8 through 40 in the fund's life. The shaded box denotes years 3 through 5 where PE participants typically expect a fundraising event to occur. The first year of reported IRRs is censored in the Cambridge Associates database. The sample attenuates in later cells.

Figure 2: Reported IRR Around Fundraising

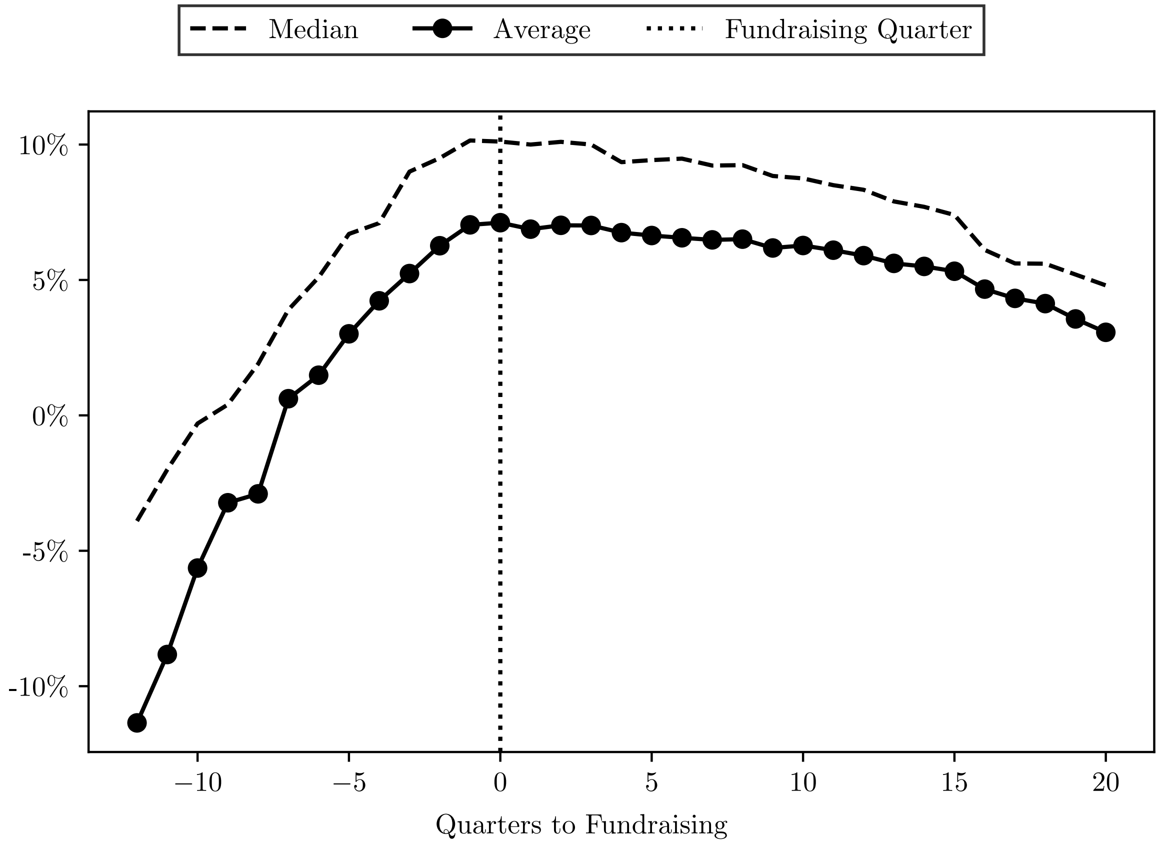

Figure 2: Plots the average and median IRRs relative to the fundraising quarter for the 416 out of 448 funds in our sample that successfully raised a subsequent fund. IRRs for each fund are annualized, net-of-fees, and "to-date" measures, reflecting expected returns over the funds' lives as of a given quarter. Fundraising quarters are defined following Brown, Gredil, and Kaplan (2019) to be the quarter of the first capital call for the next PERE fund managed by the same sponsor at least three years after the current fund's vintage year. If the follow-on fund is identified but the capital call date is missing, the fundraising quarter is assumed to be the average time to raise capital for a follow-on fund for other funds with the same vintage year.

Figure 3: IRR Manipulation Event Study

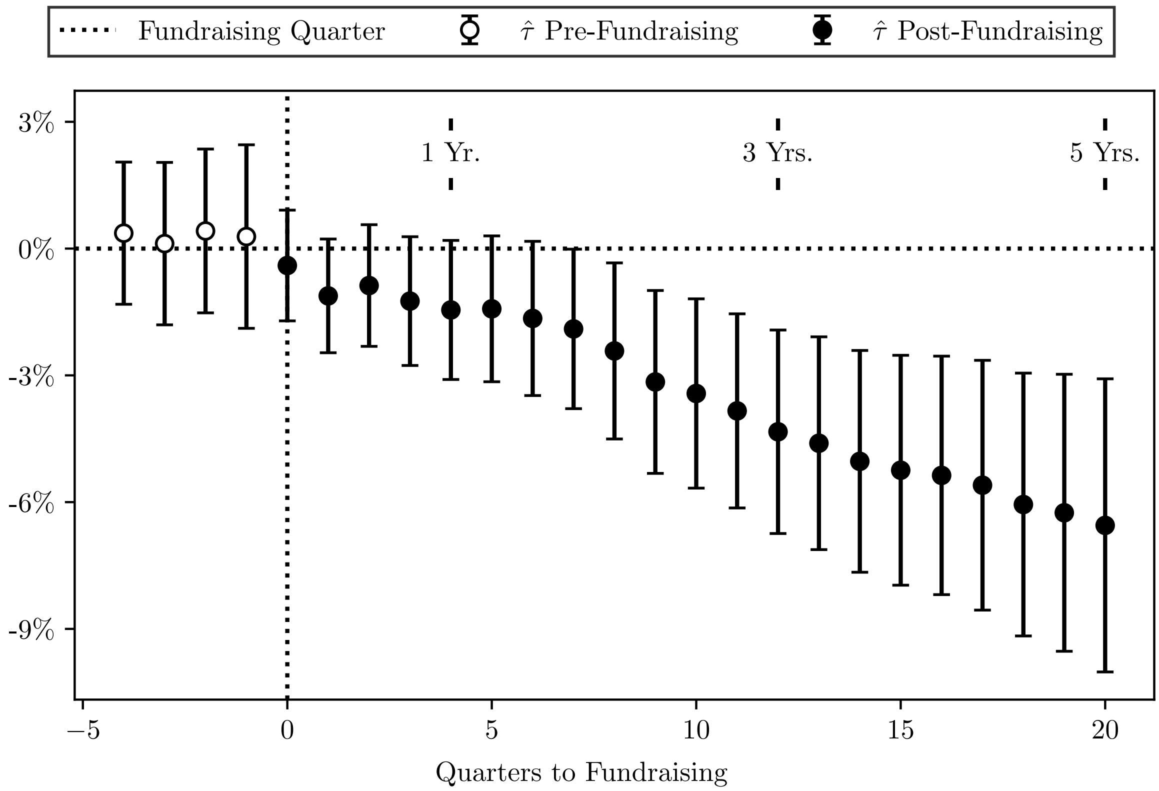

Figure 3: Plots dynamic difference-in-differences estimates of the effect of fundraising on reported IRRs using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. IRR reports for each fund are annualized, net-of-fees, and "to-date" measures, reflecting expected returns over the funds' lives as of a given quarter. Vertical lines denote 95% confidence intervals and filled circles denote point estimates of the treatment effect at each quarter relative to the fundraising event. Open circles denote pre-trend coefficient estimates. Calculations use fund and calendar time fixed effects, controls include lagged PME and lagged NAV, and standard errors are clustered at the fund level.

Figure 4: IRR Manipulation Attribution

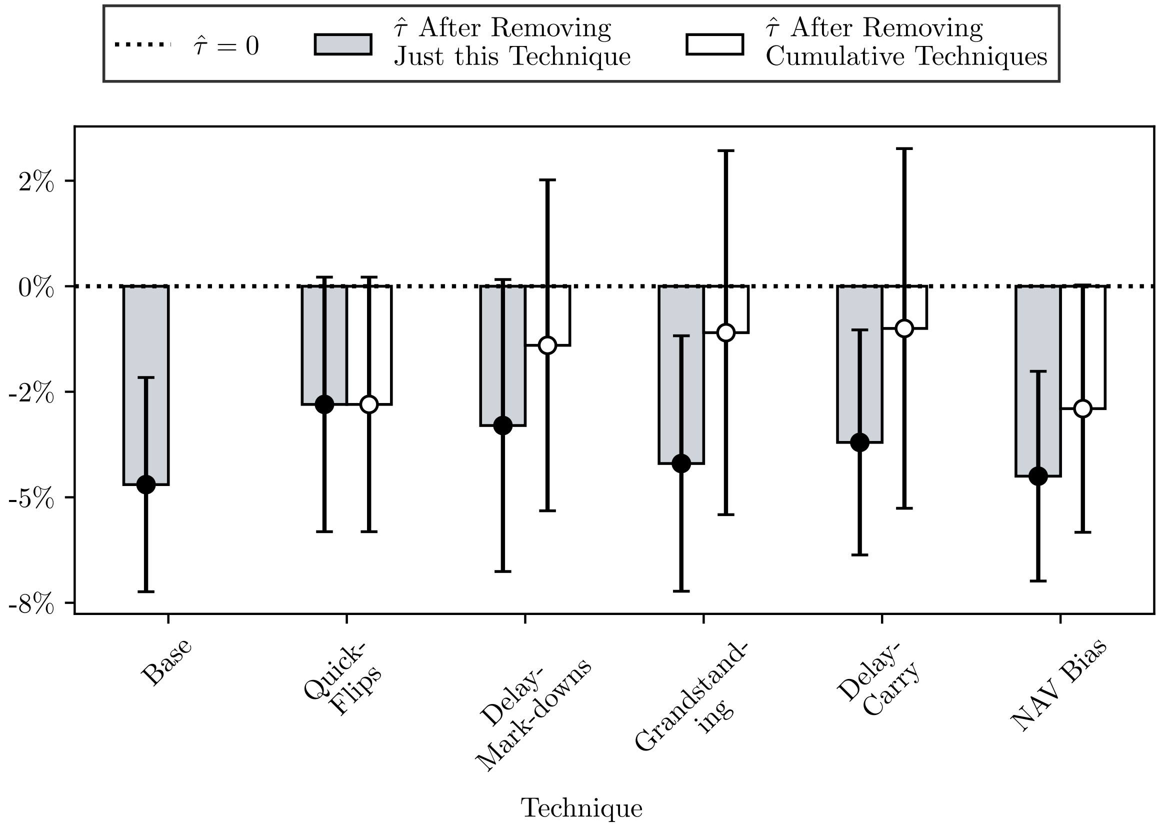

Figure 4: Plots difference-in-differences estimates of the effect of fundraising on reported IRRs, after removing funds that conform to particular window dressing techniques using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Section 4.2.1 describes each technique in detail. Filled circles denote the estimated treatment effect after accounting for an individual window dressing channel and unfilled circles denote the treatment effect after accounting for cumulatively removed window dressing channels. Vertical lines denote 95% confidence intervals. The resulting sub-samples keep all unsuccessful fundraisers. Calculations use fund and calendar time fixed effects, controls include lagged PME and lagged NAV, and standard errors are clustered at the fund level.

Figure 5: IRR Manipulations Event Studies by Investor Performance Sensitivity

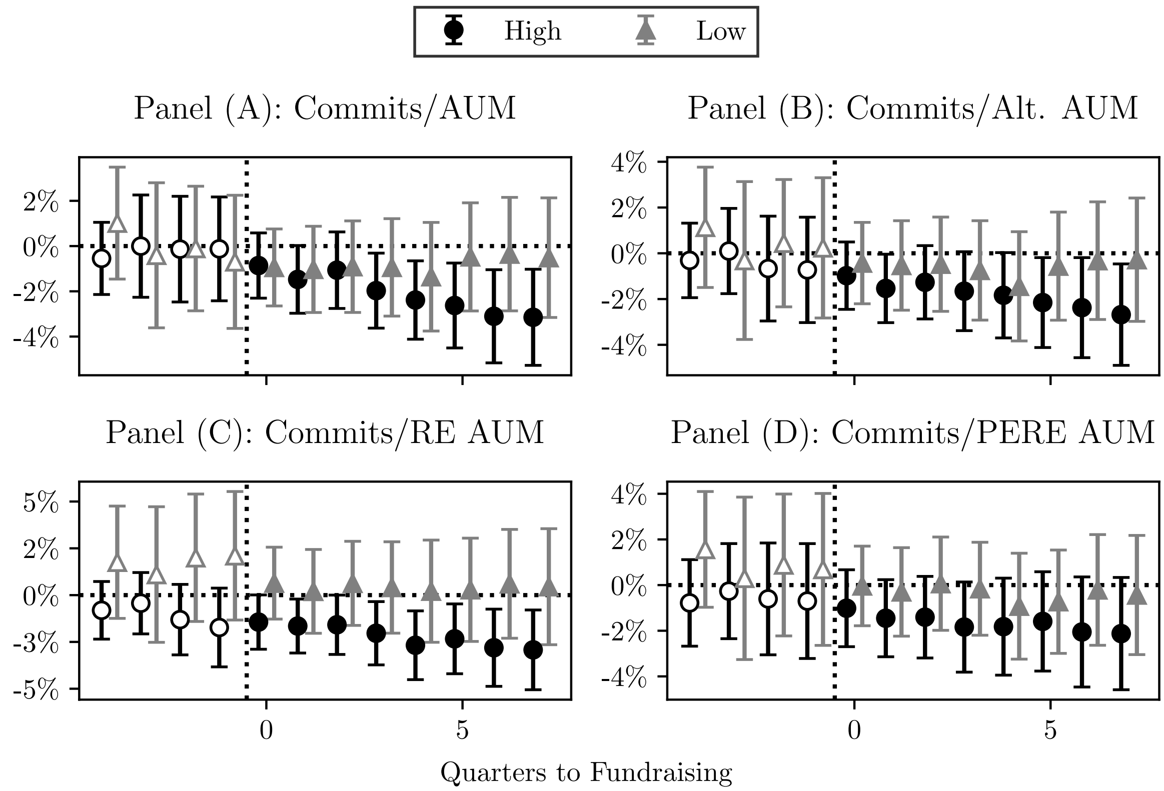

Figure 5: Plots dynamic difference-in-differences estimates of the effect of fundraising on reported IRRs, after partitioning the sample of funds on measures of investor performance sensitivity using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Panel titles indicate the investor performance sensitivity measure. "High" indicates the investor performance sensitivity measure is above the sample median and "Low" indicates the investor performance sensitivity measure is below the sample median. "Alt. Assets" includes LP AUM contained in buyout funds, venture capital funds, real estate funds, hedge funds, private debt funds, private infrastructure funds, and other *alternative* asset classes in the Preqin database. Real Estate (RE) assets are both listed and unlisted. Target allocations to private RE assets include PERE funds. The sensitivity calculations respectively contain 320, 318, 305, and 305 funds with commitments that represent at least 5% of total commitments to the corresponding fund. The resulting sub-samples keep all unsuccessful fundraisers to moderate bias from the limited never-treated observations in later calendar-time cells. Vertical lines denote 95% confidence intervals and filled circles/triangles denote point estimates of the treatment effect at each quarter relative to the fundraising event. Open circles/triangles denote pre-trend coefficient estimates. Calculations use fund and calendar time fixed effects, controls include lagged PME and lagged NAV, and standard errors are clustered at the fund level.

Table 1: Sample Composition by Vintage Year

Vintage Year	2001-2003	2004-2006	2007-2009	2010-2014	All	Preqin CRE
			Panel A: Fund Composition			
# of Funds	28	147	141	132	448	3,972
# of GPs	25	109	118	113	208	1,438
Raised a Follow-on	96.43%	90.48%	91.49%	96.21%	92.86%	73.94%
Fully Liquidated	75.00%	44.22%	28.37%	15.91%	32.81%	28.73%
First Time Fund	17.86%	23.81%	17.02%	15.15%	18.75%	30.16%
Domestic Focus	92.86%	66.67%	57.45%	68.18%	65.85%	51.46%
Main Strategy:						
Opportunistic	35.71%	46.94%	51.06%	41.67%	45.98%	31.70%
Value-Add	53.57%	45.58%	41.13%	41.67%	43.53%	34.94%
Core+	10.71%	4.76%	4.26%	8.33%	6.03%	8.76%
Distressed	0.00%	0.68%	2.84%	6.06%	2.90%	2.92%
Core	0.00%	2.04%	0.71%	2.27%	1.56%	16.47%
Main Property Type:						
Diversified	78.57%	76.87%	77.30%	70.45%	75.22%	53.44%
Office	14.29%	7.48%	4.96%	6.06%	6.70%	8.76%
Residential	0.00%	4.76%	4.96%	11.36%	6.47%	19.76%
Retail	3.57%	2.04%	4.96%	2.27%	3.13%	6.63%
Niche	0.00%	2.72%	2.13%	5.30%	3.13%	3.04%
Hotels	0.00%	3.40%	1.42%	0.76%	1.79%	2.42%
Industrial	3.57%	2.72%	4.26%	3.79%	3.57%	5.95%
			Panel B: Investor Composition			
# of LPs	158	681	778	854	1,372	2,421
# of Known Commits	208	1,880	1,873	1,952	5,921	12,993
North American	97.60%	93.67%	91.72%	91.34%	92.43%	83.23%
Investor Type:						
Private Sector Pension	28.37%	26.70%	24.88%	30.94%	27.65%	24.67%
Public Pension	28.37%	26.97%	26.96%	31.05%	28.32%	31.47%
Foundation	25.48%	18.14%	18.69%	16.03%	17.89%	15.79%
Endowment	7.21%	13.62%	14.26%	9.63%	12.26%	9.51%

Table 1: Tabulates the composition of PERE funds and investors active during the period 2001-2019. Fund data are provided by Cambridge Associates and validated using Preqin. Investor and commitment data are sourced from Preqin. The "All" column includes all funds in our sample. The "Preqin CRE" column includes all closed-end commercial real estate-focused private equity funds tracked by Preqin during our sample period. Of these 3,972 Preqin funds, 273 have cash-flow data in Preqin that satisfies restrictions used in constructing the Cambridge Associates sample of funds. Investor composition need not sum to 100% as other categories (e.g., sovereign wealth funds, insurance companies, and fund of funds) are excluded tabulations in the investor type subcategory.

Table 2: Summary Statistics

	Nobs.	Mean	Std. Dev.	5%	25%	50%	75%	95%
Panel A: Fund × Quarter								
IRR	17,017	0.02	0.20	-0.30	-0.06	0.05	0.13	0.26
TVPI	18,554	1.10	0.45	0.31	0.80	1.10	1.40	1.80
PME	18,547	0.87	0.38	0.25	0.64	0.88	1.07	1.48
DPI	18,547	0.47	0.54	0.00	0.00	0.29	0.81	1.52
RVPI	18,547	0.63	0.41	0.00	0.30	0.65	0.95	1.20
Panel B: Fund Level								
Fund Size ($MM)	448	773.51	1,198.96	73.98	236.38	460.00	800.00	2,484.35
# of Previous Funds	448	4.87	6.94	0	1	2.50	6	16.65
Vintage Year	448	2007.56	2.85	2003	2005	2007	2010	2012
Cumul. Capital Raised ($MM)	448	2,307.07	5,380.90	0	109.20	550.00	2,285.50	9,065.70
Final IRR	448	0.05	0.15	-0.14	-0.02	0.08	0.14	0.23
Final PME	448	0.86	0.38	0.19	0.59	0.91	1.10	1.45
Panel C: Fund Level LP Characteristics								
Observed Commits/Fund Size	448	22.69%	23.74%	0.00%	3.86%	15.75%	35.39%	69.60%
# of Observed LPs	421	14.06	15.41	2.00	4.00	9.00	19.00	43.00
Est. # of LPs	320	24.00	19.85	5.10	10.27	17.00	30.52	61.01
Fund HHI	320	954.06	1004.80	187.47	398.46	649.85	1112.92	2990.11
Avg. Commit/AUM	320	4.04%	11.54%	0.11%	0.42%	1.33%	3.69%	13.37%
Investor Composition								
Pct. Returning LPs	320	38.24%	27.38%	0.00%	15.79%	40.31%	58.82%	80.70%
Pct. Public Pension LPs	320	30.76%	23.39%	0.00%	13.75%	28.57%	43.37%	75.00%
Pct. Private Pension LPs	320	25.85%	18.25%	0.00%	13.20%	25.00%	36.36%	58.88%
Pct. Endowment LPs	320	11.14%	16.21%	0.00%	0.00%	5.80%	15.38%	40.85%
Panel D: Public Pension Characteristics								
Funding Ratio	446	0.78	0.16	0.54	0.66	0.79	0.89	1.05
log(1+CIO Pay)	296	12.31	0.51	11.58	11.95	12.28	12.62	13.28
log(1+Pensioner Pay)	438	10.82	0.30	10.41	10.62	10.79	11.01	11.29
CIO Relative Pay	286	1.48	0.54	0.65	1.13	1.45	1.80	2.42
Commit/Assets	1,076	0.28%	0.52%	0.05%	0.12%	0.20%	0.31%	0.82%

Table 2: Tabulates summary statistics for the main variables in our study. Panel A is tabulated at the fund × quarter level and Panels B and C are tabulated at the fund level. Quarterly performance reports for each fund are "to-date" measures, reflecting expected returns over the funds' lives as of a given quarter. IRRs are annualized. Fund level LP characteristics in Panel C are only tabulated for funds in which the sum of known LP commitments equals at least 5% of the total fund size. Commit/Assets in Panel D are tabulated at the commitment-pension-year level using the actuarial value of assets. Remaining variables in Panel D are tabulated at the pension-year level conditional on a commitment to a fund in a given vintage year. The PME benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs.

Table 3: Return Manipulation and Falsification Tests

	(1) IRR	(2) TVPI	(3) PME	(4) DPI	(5) RVPI
Panel A: Difference-in-Differences Estimates					
$\hat{\tau}$	-0.047***	0.066	0.026	0.174***	-0.108***
	(-3.63)	(1.53)	(0.82)	(4.48)	(-3.97)
N	16,968	18,103	18,100	18,100	18,100
Panel B: Placebo Difference-in-Differences Estimates					
$\hat{\tau}$ Random Treatment	0.025*	0.080**	0.031	0.060*	0.020
	(1.92)	(2.44)	(1.15)	(1.82)	(0.89)
N	16,413	17,704	17,701	17,701	17,701
$\hat{\tau}$ Random Timing	-0.004	0.132***	0.098***	0.123***	0.009
	(-0.33)	(4.29)	(4.19)	(3.95)	(0.38)
N	14,591	16,968	16,965	16,965	16,965
$\hat{\tau}$ Random Treatment & Timing	0.023*	0.086**	0.041*	0.036	0.050**
	(1.84)	(2.92)	(1.75)	(1.19)	(2.33)
N	15,537	17,429	17,426	17,426	17,426
All specifications include: fund FE, calendar time FE, and controls					

Table 3: Panel A reports difference-in-differences estimates of the effect of a successful fundraising on key performance metrics using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. The estimating equation is: $\hat{\tau} = \sum w_{it}(y_{it} - \hat{y}_{it}(0))$, where $\hat{\tau}$ denotes the estimated treatment effect, y_{it} denotes the observed performance variable in the post-fundraising period, and $\hat{y}_{it}(0))$ denotes the estimated counterfactual (imputed) performance variable based on the set of observations where the fund manager has not yet or never called capital for a follow-on fund. Quarterly performance reports for each fund are "to-date" measures, reflecting expected returns over the funds' lives as of a given quarter. Panel B randomizes (a) fundraising success, (b) fundraise timing, and (c) both fundraising success and timing and reports difference-in-differences estimates of the effect of a successful fundraising on key performance metrics using the Borusyak, Jaravel, and Spiess (2021) estimator. All specifications include fund and calendar time fixed effects, and lagged PME and NAV as controls. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 4: IRR Manipulation Attribution

	Base	Quick Flips	Delay Mark-Downs	Grand-standing	Delay Carry	NAV Bias
		Difference-in-Differences Estimates After Removing:				
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Individual Manipulation Techniques						
$\hat{\tau}$ IRR	-0.047***	-0.028*	-0.033*	-0.042***	-0.041***	-0.045***
	(-3.63)	(-1.82)	(-1.87)	(-2.72)	(-3.04)	(-3.55)
N	16,968	11,431	11,341	12,136	16,968	11,666
Panel B: Cumulative Manipulation Techniques						
$\hat{\tau}$ IRR	-0.047***	-0.028*	-0.014	-0.011	-0.013	-0.031**
	(-3.63)	(-1.82)	(-0.70)	(-0.50)	(-0.63)	(-2.15)
N	16,968	11,431	7,552	6,368	6,368	5,225
All specifications include: fund FE, calendar time FE, and controls						

Table 4: Reports difference-in-differences estimates of the effect of a successful fundraising on IRRs, **not** attributable to each manipulation technique using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Section 4.2.1 describes techniques in detail. Panel A reports the recalculated treatment effect after removing funds whose behavior conforms to the window dressing technique in the column. Panel B reports the recalculated treatment effect after removing funds consistent with all techniques to the left of, and including, the one listed in the current column. The right-most column of Panel B reports the treatment effect after accounting for all window dressing techniques simultaneously, whereas the rightmost column of Panel A is the treatment effect after removing only the last-listed window-dressing technique. The resulting sub-samples keep all unsuccessful fundraisers to moderate bias from the limited never-treated observations in later calendar-time cells. The unit of observation is fund-quarter. All specifications include fund and calendar time fixed effects, and lagged PME and NAV as controls. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 5: IRR Manipulation and Investor Performance Sensitivity

Investor Performance Sensitivity Measure	Ratio of Commitments to AUM		Ratio of Commitments to AUM in Alt. Assets		Ratio of Commitments to Target AUM in RE Assets		Ratio of Commitments to AUM in Private RE Assets	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{\tau}$ IRR	-0.064***	-0.011	-0.057***	-0.018	-0.066***	-0.002	-0.054***	-0.007
	(-4.36)	(-0.59)	(-3.63)	(-0.96)	(-4.22)	(-0.11)	(-3.17)	(-0.37)
N	6,937	7,204	7,017	7,044	6,756	6,853	6,811	6,758

All specifications include: fund FE, calendar time FE, and controls

Table 5: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by measures of investor elasticity to fund returns using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Investor performance sensitivity at the fund level (i) is calculated as:

$$\text{Investor Performance Sensitivity}_i = \frac{1}{J}\sum_{j\leq J}\frac{c_{ij}}{AUM_j},$$

where J denotes the number of known investors in the fund, c_{ij} is the commitment made by each LP (often imputed), and AUM_j is calculated according to column headers. "High" indicates the sensitivity measure is above the sample median and "Low" indicates the sensitivity measure is below the sample median. "Alt. Assets" includes LP AUM contained in buyout funds, venture capital funds, real estate funds, hedge funds, private debt funds, private infrastructure funds, and other *alternative* asset classes in the Preqin database. Real Estate (RE) assets are both listed and unlisted. Target allocations to private RE assets include PERE funds. All commitment and AUM data are retrieved from Preqin in February 2022. The sensitivity calculations respectively contain 320, 318, 305, and 305 funds with requisite data and commitments that represent at least 5% of total fund commitments in Preqin. The resulting sub-samples keep all unsuccessful fundraisers to moderate bias from the limited never-treated observations in later calendar-time cells. The unit of observation is fund-quarter. All specifications include fund and calendar time fixed effects, and lagged PME and NAV as controls. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 6: Determinants of Public Pension Investor Allocations

	100 × Commitment/Assets				
	(1)	(2)	(3)	(4)	(5)
Funding Ratio	-0.341***			-0.259***	-0.234***
	(-4.97)			(-3.01)	(-2.88)
$\log(\frac{1+\text{CIO Pay}}{1+\text{Pensioner Pay}})$		-0.104***		-0.075***	
		(-5.82)		(-4.63)	
log(1+ CIO Pay)			-0.119***		-0.091***
			(-7.47)		(-6.16)
Constant	0.508***	0.385***	1.694***	0.544***	1.536***
	(8.65)	(9.23)	(8.56)	(8.32)	(9.20)
Controls	x	x	x	x	x
Year FE	x	x	x	x	x
Adj. R^2	0.097	0.149	0.182	0.190	0.215
N	1,039	696	714	696	714

Table 6: Regresses the share of assets committed to a given PERE fund on characteristics of the pension and the compensation of the pension plan's Chief Investment Officer (CIO). Pension assets and liabilities are measured according to General Accounting Standards Board (GASB) statement 25. *Funding Ratios* are calculated by dividing actuarial assets by actuarial liabilities, also following GASB 25. $\log(\frac{1+\text{CIO Pay}}{1+\text{Pensioner Pay}})$ is the log ratio of CIO total compensation to the average salary of beneficiaries of the same pension plan. Pension variables are as of the the PERE fund's vintage year. Fund level allocations are provided by Preqin, pension level variables are provided by the Public Plans Database (PPD), and CIO compensation data are provided by Lu, Mullally, and Ray (2021). Pension fund data are pooled at the board level when mapping to Preqin. Controls include the pension's total returns in the previous year and CIO tenure. Standard errors are clustered at the pension fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 7: IRR Manipulation by Investor and Fund Characteristics

Panel A: Investor Characteristics

	Past Performance		# Previous Investments with GP		# Previous PERE Investments	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\tau}$ IRR	-0.052**	-0.021	-0.050***	-0.025	-0.033*	-0.030
	(-2.42)	(-1.32)	(-3.12)	(-1.24)	(-1.83)	(-1.58)
N	6,982	7,122	7,281	6,823	7,553	6,588

Panel B: Fund Characteristics

	GP Reputation		Fund HHI		Fund Risk	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\tau}$ IRR	-0.037**	-0.049***	-0.025	-0.045***	-0.052***	-0.022
	(-2.42)	(-3.00)	(-1.29)	(-2.75)	(-3.42)	(-1.18)
N	6,513	11,666	7,025	7,116	8,990	9,189

Table 7: Tabulates the difference-in-differences estimates of the effect fundraising on reported IRRs, after partitioning the sample by investor and fund characteristics using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Panel A partitions the sample using measures of investor sophistication defined in section 4.4.1 and Panel B partitions the sample using fund characteristics defined in section 4.4.2. The resulting sub-samples keep all unsuccessful fundraisers to moderate bias from the limited never-treated observations in later calendar-time cells. The cross-sections relying on investor characteristics include the 320 out of 448 funds in our sample where the sum of known commitments in Preqin account for at least 5% of total commitments for the fund. The unit of observation is fund-quarter. All specifications include fund and calendar time fixed effects, and lagged PME and NAV as controls. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 8: IRR Manipulation, Investor Performance Sensitivity, and Investor Composition

Investor Performance Sensitivity Measure	Ratio of Commitments to AUM		Ratio of Commitments to AUM in Alt. Assets		Ratio of Commitments to Target AUM in RE Assets		Ratio of Commitments to AUM in Private RE Assets	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Past Performance (TVPI)								
High	-0.086***	-0.012	-0.074***	-0.039	-0.086***	-0.011	-0.092***	0.009
	(-5.22)	(-0.38)	(-4.16)	(-1.33)	(-4.05)	(-0.38)	(-4.61)	(0.28)
N	4,259	3,934	4,408	3,749	4,213	3,690	4,154	3,666
Low	-0.037*	-0.013	-0.041*	0.004	-0.040**	0.000	-0.020	-0.006
	(-1.88)	(-0.74)	(-1.93)	(0.21)	(-2.12)	(0.01)	(-0.89)	(-0.40)
N	3,852	4,481	3,807	4,482	3,717	4,374	3,831	4,303
# of Previous Investments with the Same GP								
High	-0.055***	-0.023	-0.051***	-0.024	-0.073***	-0.011	-0.062***	-0.014
	(-3.24)	(-1.07)	(-2.85)	(-1.23)	(-3.57)	(-0.60)	(-3.33)	(-0.70)
N	4,750	3,742	5,078	3,414	4,509	3,868	4,846	3,545
Low	-0.068***	-0.008	-0.062***	-0.010	-0.051***	-0.005	-0.056***	0.004
	(-3.65)	(-0.38)	(-3.05)	(-0.47)	(-3.19)	(-0.19)	(-2.67)	(0.17)
N	3,361	4,673	3,137	4,817	3,421	4,196	3,139	4,424
# of Previous PERE Investments								
High	-0.048**	-0.020	-0.038	-0.026	-0.064**	-0.013	-0.030	-0.026
	(-2.21)	(-0.97)	(-1.61)	(-1.30)	(-2.51)	(-0.64)	(-1.10)	(-1.34)
N	3,601	5,163	3,713	4,971	3,321	5,048	3,567	4,667
Low	-0.061***	-0.002	-0.058***	-0.002	-0.059***	-0.005	-0.063***	0.007
	(-4.07)	(-0.10)	(-3.47)	(-0.09)	(-3.88)	(-0.21)	(-3.96)	(0.38)
N	4,547	3,252	4,502	3,297	4,646	3,016	4,455	3,302
All specifications include: fund FE, calendar time FE, and controls								

Table 8: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by measures of investor sensitivity to fund returns and on investor characteristics using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. The resulting sub-samples keep all unsuccessful fundraisers to moderate bias from the limited never-treated observations in later calendar-time cells. The unit of observation is the fund-quarter. All specifications include fund and calendar time fixed effects, and lagged PME and NAV as controls. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 9: IRR Manipulation, Investor Performance Sensitivity, and Fund Characteristics

Investor Performance Sensitivity Measure	Ratio of Commitments to AUM		Ratio of Commitments to AUM in Alt. Assets		Ratio of Commitments to Target AUM in RE Assets		Ratio of Commitments to AUM in Private RE Assets	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GP Reputation								
High	-0.049***	-0.002	-0.055***	0.006	-0.064***	0.013	-0.047***	-0.001
	(-2.84)	(-0.08)	(-2.94)	(0.31)	(-3.67)	(0.62)	(-2.61)	(-0.06)
N	3,821	3,434	3,935	3,320	3,872	3,383	3,968	3,249
Low	-0.067***	-0.026	-0.054***	-0.037*	-0.065***	-0.027	-0.064***	-0.012
	(-3.73)	(-1.15)	(-2.69)	(-1.67)	(-2.93)	(-1.21)	(-3.01)	(-0.50)
N	4,327	4,981	4,280	4,948	4,095	4,681	4,054	4,720
Fund HHI								
High	-0.065***	-0.011	-0.053***	-0.010	-0.072***	-0.001	-0.069***	-0.001
	(-3.66)	(-0.50)	(-2.85)	(-0.41)	(-4.25)	(-0.06)	(-3.73)	(-0.04)
N	3,402	4,834	3,400	4,756	3,159	4,599	2,892	4,826
Low	-0.058***	-0.015	-0.055***	-0.019	-0.061***	-0.011	-0.051**	-0.015
	(-3.63)	(-0.60)	(-3.14)	(-0.90)	(-3.32)	(-0.52)	(-2.58)	(-0.73)
N	4,746	3,581	4,815	3,512	4,808	3,465	5,130	3,143
Fund Risk								
High	-0.062***	-0.022	-0.058***	-0.024	-0.065***	-0.028	-0.067***	-0.022
	(-3.18)	(-1.10)	(-2.99)	(-1.12)	(-3.41)	(-1.41)	(-3.45)	(-1.15)
N	4,180	3,810	4,190	3,800	3,881	3,886	3,895	3,894
Low	-0.049***	-0.001	-0.037*	-0.004	-0.054***	0.010	-0.037*	0.013
	(-2.95)	(-0.03)	(-1.90)	(-0.21)	(-2.58)	(0.42)	(-1.65)	(0.59)
N	3,968	4,605	4,025	4,468	4,086	4,178	4,127	4,075

All specifications include: fund FE, calendar time FE, and controls

Table 9: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by measures of investor sensitivity to fund returns and fund characteristics using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. The resulting sub-samples keep all unsuccessful fundraisers to moderate bias from the limited never-treated observations in later calendar-time cells. The unit of observation is fund-quarter. All specifications include fund and calendar time fixed effects, and lagged PME and NAV as controls. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

A Appendix

Figure A1: Composition by Fundraising

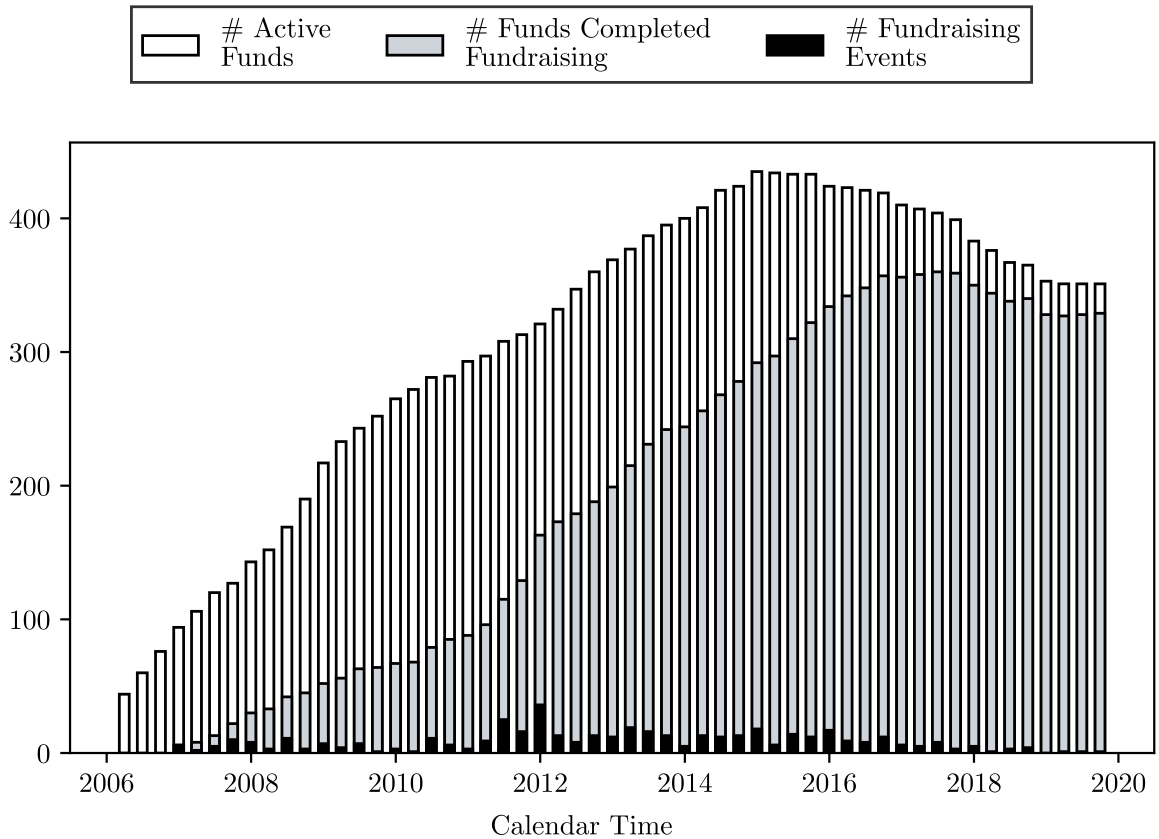

Figure A1: Plots the number of funds in each year-quarter in our sample where the GP reports IRR and (a) has not called capital for a successor fund, (b) has called capital for a follow-on fund, or (c) makes the first capital call for a follow-on fund. Throughout, we interpret the first capital call in the follow-on fund as marking the completion of fundraising, following Barber and Yasuda (2017) and Brown, Gredil, and Kaplan (2019).

Figure A2: Empirical Distribution of Fundraising Events

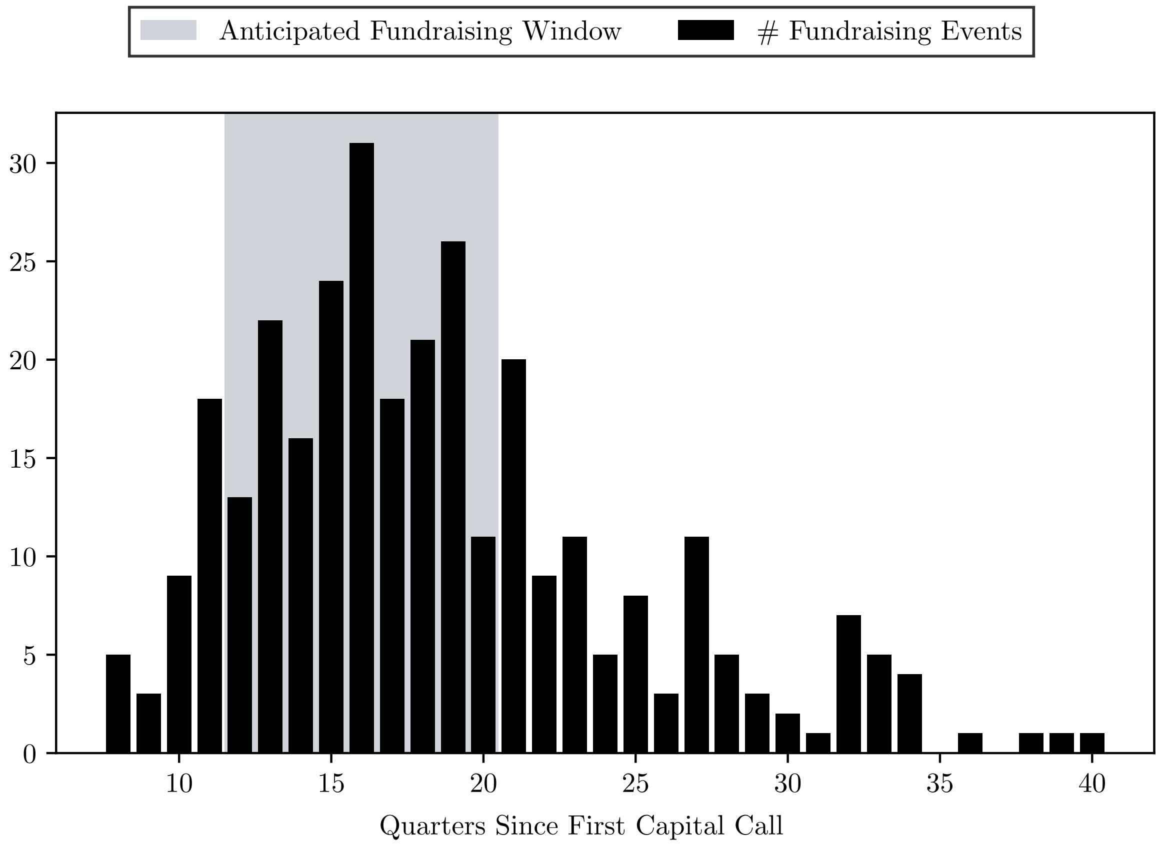

Figure A2: Plots the empirical distribution of fundraising events since inception for the 315 out of 448 funds in our sample that successfully raised a subsequent fund and where the exact quarter of the successor fund's first capital call is observed. The plot is restricted to quarters 8 through 40 in the fund's life. The shaded box denotes years 3-5 where PE participants typically expect a fundraising event to occur. Fundraising quarters are defined following Brown, Gredil, and Kaplan (2019) to be the quarter of the first capital call for the next PERE fund managed by the same sponsor at least three years after the current fund's vintage year.

Table A1: Example Successor Fund Provisions

Institutional Limited Partners Association (ILPA) Model Terms 2020: Section 9.1	*"Until the earliest of (i) the termination of the Commitment Period, (ii) the date when 80% of Commitments have been funded, invested, committed or reserved for investments (including Follow-on Investments) or funded or reserved for Fund Expenses; (iii) the date when 60% of Commitments have been funded for investments; and (iv) the termination of the Fund, the General Partner and the Fund Manager shall not, and hereby commit that none of their Affiliates shall, directly or indirectly, accrue any management or advisory fees relating to any vehicle or account (other than any Fund Vehicle), having investment objectives that materially overlap with the Investment Objectives ("Successor Fund"), in each case except with the prior written consent of a Majority in Interest".* (Source: https://bit.ly/3DEIfyQ)
Christopher M. Schelling 2016 Article	Example 1: *"The Managing Directors may form any successor private equity fund with objectives substantially similar to the Partnership (a "Successor Fund") on or after the earliest to occur of (i) such time as at least 75% of the Partnership's Committed Capital has been invested, committed or reserved for investment in Portfolio Companies, or applied, committed or reserved for Partnership working capital or expenses or (ii) the expiration or permanent suspension of the Investment Period".* Example 2: *"Unless consented to by (i) the Advisory Board, or (ii) at least 66 2/3% in Interest of the Limited Partners, from the Initial Closing Date through the earlier of (a) the expiration or termination of the Commitment Period, or (b) the date on which at least 75% of the aggregate Commitments of the non-defaulting Partners has been invested, committed to be invested (or reserved for investments in Follow-On Investments) or reserved for payment of Fund Expenses, including, without limitation, the Management Fee, none of the General Partner, the Management Company or any of their respective affiliates will close on any new investment fund vehicle controlled or managed by the General Partner, the Management Company or any of their respective Affiliates and which has substantially similar investment objectives as the Fund".* (Source: https://bit.ly/3qW4FGC)

Table A1: Transcribes language seen in fund governance documents– Limited Partnership Agreements– that restrict when general partners can raise successor funds.

Table A2: Manipulation Techniques

Technique		Details about Technique and Precedent
Quick Flips	• Description	Exit better investments earlier,thereby holding worse investments longer
	• Measurement	Top tercile of average scaled distributions per year during fundraising or RVPI $< .05$
	• Closest Relative(s)	Phalippou (2008) and Lopez-de-Silanes, Phalippou, and Gottschalg (2015)
Delay Mark-downs	• Description	Wait until after fundraising to reveal bad investments
	• Measurement	Top tercile of mark-downs the year following fundraising
	• Closest Relative(s)	Barber and Yasuda (2017) and Chakraborty and Ewens (2018)
Grandstanding	• Description	Make large distributions before fundraising to signal skill
	• Measurement	Top tercile of scaled distribution growth the year before fundraising
	• Closest Relative(s)	Gompers (1996)
Delay Carry	• Description	Defer carry receipt to boost IRR
	• Measurement	Indicator if a fund qualifies for carry but has yet to make requisite distributions
	• Closest Relative(s)	Robinson and Sensoy (2013)
NAV Bias	• Description	Overstate the value of ongoing investments
	• Measurement	Top tercile of Brown, Gredil, and Kaplan (2019) $NAVbias$ the year before fundraising
	• Closest Relative(s)	Brown, Gredil, and Kaplan (2019)

Table A2: Describes several techniques by which GPs could manipulate fund-level net-of-fee IRRs around fundraising.

Internet Appendix for: Catering and Return Manipulation in Private Equity

December 15, 2022

A Cash Flow Imputations

In this section, we present the explicit transformations used to impute quarterly cash flows with only performance data. We then validate our imputation. Throughout our paper, we use this imputation to calculate Public Market Equivalents (PMEs) and Net Asset Values (NAVs) that traditionally require cash-flow data. Our primary innovation is to exploit quarterly changes in performance measures to impute the cash flows and valuation changes that occur in any given quarter. Because PE performance metrics are functions of PE cash flows and underlying portfolio investment valuations, they can be rearranged to calculate cash flows and NAVs that would otherwise correspond to each quarterly report.

There are three missing components of cash-flow data in our CA dataset; quarterly calls from LPs, quarterly distributions to LPs, and the quarterly Net Asset Value of the assets held in a fund. We impute quarterly calls (C) as the change in percent called (PC) multiplied by the level of committed capital for fund i in quarter t:

$$C_{it} = F_i \times (PC_{it} - PC_{i,t-1}), \tag{1}$$

where F_i denotes the size of the fund. Intuitively, equation (1) recovers the level of capital called in a given quarter t if the level of capital committed to the fund is fixed. We assume calls in the first quarter ($t = 0$) equal the percent called at time $t = 0$ multiplied by fund size. A unique aspect of the CA data is that percent called levels are given in quartiles rather than percentages, i.e., quartile 1 corresponds to a percent called between 0 and 25%. We assume calls proceed uniformly in each quartile, which closely corresponds to cash-flow profiles in Preqin. For example, if CA reports "Q1" for the first four quarters of a fund's life, we assume 6.25% (= 25%/4) of committed capital was called each of the four quarters. However, our results are robust to permutations of this procedure where calls occur more discretely, such as using midpoints or assuming calls occur at the beginning or end of a quartile transition.

We impute quarterly distributions to LPs (D) as the change in Distributions to Paid in Capital (DPI) multiplied by the level of called capital for fund i in quarter t:

$$D_{it} = F_i \times (DPI_{it} \times PC_{it} - DPI_{i,t-1} \times PC_{i,t-1}). \tag{2}$$

We scale fund size by percent called to account for the fact that the DPI calculation uses called capital, rather than committed capital, as the denominator. We assume distributions, if any, in the first quarter ($t = 0$) equal DPI at time $t = 0$ multiplied by the level of called capital. Lastly, we impute quarterly net asset values by converting the residual value to paid-in capital (RVPI) to a dollar amount:

$$NAV_{it} = F_i \times PC_{it} \times \underbrace{(TVPI_{it} - DPI_{it})}_{RVPI_{it}}. \tag{3}$$

Since NAV is a stock, rather than a flow, there is no need to use changes in quarterly performance metrics for our imputation. Table IA3 provides a numerical example of our imputation for a fund of size \$100.

We also present a simple validation of our algebraic identities. We calculate to-date IRRs each quarter using the imputed cash-flows and NAVs described above and compare these *imputed IRRs* to the actual net IRRs reported each quarter in the CA database. For reference, the to-date IRR for fund i in quarter t solves:

$$0 = \sum_{\tau=0}^{\tau=t} \frac{Distribution_{i\tau} - Call_{i\tau}}{(1 + IRR_{it})^t} + \frac{NAV_{it}}{(1 + IRR_{it})^t}.$$

Figure IA3 plots the average actual IRR and imputed IRR for the 448 funds over the course of each fund's life for all quarters where the absolute value of both interim metrics is less than 100%. This plot makes clear that the two are very similar.

B Commitment Data Imputations

The Preqin commitment data are missing both (1) commitments for some known LPs and (2) the commitments for unknown LPs. As a further complication, the true quantity of LPs is unknown. In this section, we detail and validate our method for estimating the number of Limited Partners, and corresponding commitments made by each LP, in each fund. While we rely on these imputations for our main cross-sectional specifications, we ensure our cross-sectional results are not driven by imputed values. Put differently, our main results are similar if we repeat cross-sectional tests without making these imputations (i.e., Table IA17).

To formalize the problem, we decompose the observed fund size (F) into (1) the sum of known commitments made by known LPs, (2) the sum of unknown commitments made by known LPs, and (3) the sum of unknown commitments made by unknown LPs:

$$F = \underbrace{\sum_{j=1}^{j=L^N} c_j}_{\text{Observed}} + \underbrace{\sum_{k=1}^{k=L^K} c_k}_{\text{Missing Commits}} + \underbrace{\sum_{k=L^K+1}^{k=L^K+L^M+1} c_k}_{\text{Missing Commits \& LPs}} . \tag{4}$$

Our estimation algorithm proceeds as follows. First, we assume the average of unknown commitments equals the average of known commitments. For ease of notation, define the average of known commitments as $a(L^N)$. Next, as a first pass at imputing the values, we estimate the missing commitments in a simplified case assuming the number of missing LPs is zero ($L^M = 0$). In this case, we are assuming that Preqin data accounts for every LP that made a commitment to the fund, but may be missing the commitment values of some of these LPs. After the first step of our algorithm, the total value of commitments is equal to:

$$\tilde{F} = \sum_{j=1}^{j=L^N} c_j + (L^K \times a(L^N)), \tag{5}$$

where every quantity in equation (5) is known. If $F = \tilde{F}$, then our estimation for this fund stops here. However, for most funds, we observe that either $\tilde{F} < F$ or $\tilde{F} > F$ and our estimation proceeds to a second step. In the second step, we adjust commitment values and the number of LPs such that the implied fund value equals the observed fund value. In the first case, if $\tilde{F} < F$, we assume that the number of missing LPs exceeds zero. We then calculate L^M as the number of unknown LPs needed such that the average of known commitments multiplied by $L^M + L^K + L^N$ equals the observed fund size. In the second case, if $\tilde{F} > F$, we then assume the average of known commitments overstates the average of unknown commitments. In this case, we leave the number of estimated unknown LPs at zero ($L^M = 0$) and evenly divide the unaccounted for commitments among the known LPs with missing commitments. Putting the three cases together, our estimation of (*unknown* *commitment values, # of missing LPs*) is analytically reduced to a piece-wise function of known quantities:

$$(c_k, L^M) = \begin{cases} \left(a(L^N), \dfrac{F}{a(L^N)} - L^N\right), & \text{if } \tilde{F} < F, \\ \\ \left(\dfrac{F - \sum_{j=1}^{j=L^N} c_j}{L^K}, 0\right), & \text{if } \tilde{F} \geq F \end{cases}. \tag{6}$$

Table IA4 presents an example of our method solutions for (c_k, L^M) for a fund of size $F = 100$, with $L^N = 5$, $L^K \in \{0, 2\}$, and varying levels of observed commitments. In the extreme case, where the sum of known commitments equals the fund size, our estimation is trivial. We add no LPs as the data accounts for all known commitments. Moving down in Table IA4, the first case where $L^K > 0$ adds zero extra LPs because the average known commitments appear to be sufficiently large. However, in the most extreme case, where the five observed LPs (three of which had commitment data) only contributed a total of 1, the implied total number of LPs to be added is 295.

Intuitively, our estimation technique is primarily limited by the depth and quality of our commitment data (as illustrated by the last row of Table IA4). Funds rarely have more than 100 LPs and, depending on the year, are not allowed to have more than 499 LPs for at least part of our sample. However, our method can easily assign a fund to have many LPs if commitment data is sufficiently sparse. Accordingly, we restrict our sample to only include funds where the sum of known commitments equals at least 5% of the observed fund size. In doing so, we seem to alleviate the case where observed LPs may severely overstate the true number of LPs implied by our algorithm.

We also simulate the commitment data for $10,000$ funds to provide a validation of our estimation. We approximate the data provided by Preqin by first randomly allowing only some of the total number of LPs $\sim Uniform_i[2, 100]$ within a fund to be observable. We then allow only the commitments of a fraction of known LPs to be observable ($\sim Uniform_i[2, \#LPs]$). We further randomly allow ourselves to view only some fraction $\alpha_i \in (0, 1]$ of the commitments made by the observable LPs in each fund. This last restriction is meant to replicate institutional preferences for some LPs to hide their commitments. With our simulated data in hand, we then estimate the true number of LPs and their commitments in each fund using the method developed in equation (6).

Table IA5 presents a summary of our simulation results. Our simulation suggests that our imputation procedure performs well along at least two dimensions. First, our procedure appears to more accurately recover the dispersion of investors within a fund. We compare the Herfindahl-Hirschman Index (HHI) using estimated commitments to the HHI using the true, but hidden, commitments. The correlation between HHI using the simulated true data and the known commitments is only 0.12. In contrast, the correlation between HHI using the simulated true data and our imputation procedure is 0.95. Second, the correlation between the number of LPs using the simulated true data and the known commitments is only 0.59. In contrast, the correlation jumps to 0.99 after applying our imputation procedure. These disparities in correlations show our estimation significantly improves our data quality on both the HHI and number of LP dimensions in our simulated setting.

C Sample Construction for Other Asset Classes

We construct separate samples of buyout and venture funds using Preqin cash flow data for further analysis. Because the filters and sequencing adopted in this analysis are coarser than those adopted in our main analysis, we additionally replicate our PERE analysis under the same coarser filtering and sequencing as a benchmark. These samples apply for Tables IA19 and IA20.

We limit our analysis to closed-end funds with inception dates from 2001 to 2014, giving the latest sponsors seven years to raise a follow-on and at least five years to unwind any window dressing. To mimic our main analysis, we restrict this analysis to years 2006-2019. We additionally restrict our sample to funds with at least 20 quarters of consecutive reported IRRs that must be available before, during, and after the fundraising quarter. Our resulting sample contains 770 buyout, 247 venture, and 198 real estate funds. 69 of the 198 PERE funds are also in our main sample and 159 of the 198 PERE funds are in the sample of 311 PERE funds used to construct estimates in Table IA15.

Our fund sequencing relies on the extensive Preqin universe and follows that of Brown, Gredil, and Kaplan (2019). A follow-on fund is the first fund of the same asset class, raised by the same manager, at least three years after a fund's first capital call. Similar to our main sample, we impute fundraising dates within each asset class and vintage year using the median number of quarters elapsed for successful fundraisers of the same vintage. Unlike our main sample, we do not employ manual validation of these fundraising success rates. The fundraising success rates are respectively 94%, 81%, and 92% for the buyout, venture, and real estate funds in this Preqin sample.

Table IA19 displays summary statistics in terms of size and performance by asset class for the funds in this alternate sample. As in our CA sample, all performance metrics are net of fees and reported "to-date," reflecting the expected return over the fund's life as of a given quarter. To-date Public Market Equivalents (PMEs) are calculated for each quarterly report using the Brown et al. (2019) interim PME formula with the S&P 500 as a benchmark. Given both a different benchmark and set of funds, PERE funds in this sample perform slightly better than the PERE funds in our primary sample, although still materially worse than the selected benchmark. Average PMEs across each asset class are closely in line with recent statistics reported for 2002-2018 vintages in Andonov, Kräussl, and Rauh (2021). The Preqin cash flow sample does not appear to oversample better-performing funds. Among the 69 PERE funds in our main CA sample, the average final net IRR is 9.83% and the average final net IRR of the remaining PERE funds is 8.55%. The difference between the average final IRRs in the two samples is not statistically significant.

As a point of clarification, the results for PERE funds in Table IA15 are constructed with a different sample than the results in Table IA20. This gives us three different (albeit partially overlapping) sets of PERE funds from which to confirm robustness: CA and two subsets of Preqin cash-flow data. The two Preqin PERE samples differ because Table IA15 does not apply the 2006-2009 filter and because fundraising success results were manually confirmed for the sample in Table IA15 but not for the sample in Table IA20.

Internet Appendix References

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Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs. *Quarterly Journal of Economics*, *134* (3), 1405–1454.

D Additional Figures and Tables

Figure IA3: Imputed and Actual IRRs

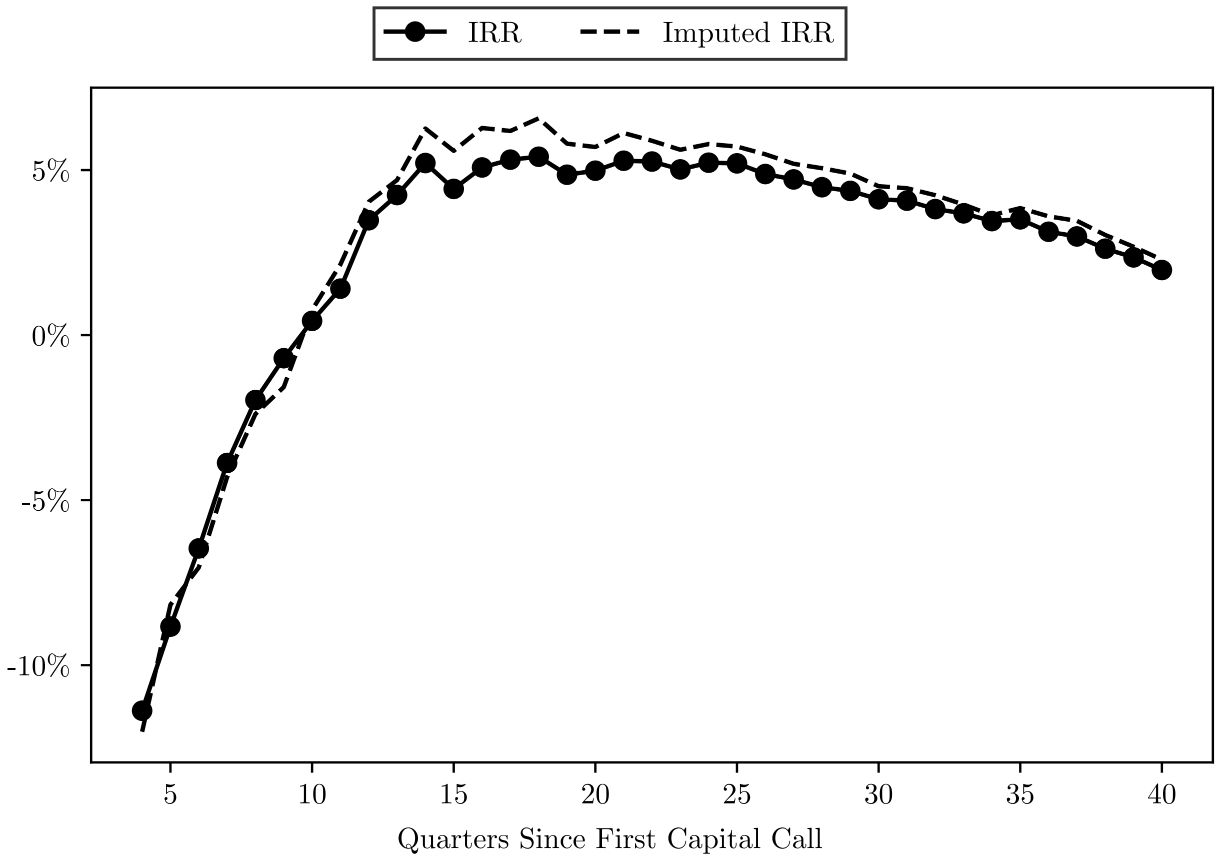

Figure IA3: Plots the average reported and imputed net IRRs since the first capital call for the 448 funds in our sample. Imputed IRRs are calculated using imputed cash-flows and Net Asset Values derived in Section A. The plot is restricted to quarters 4 through 40 in the fund's life. The first year of reported IRRs is censored in the Cambridge Associates database. The sample attenuates in later cells.

Table IA3: Cash Flow Imputation Example

	Observed Performance Metrics				Imputed Cash Flows		
Quarter	Percent Called	TVPI	DPI	RVPI	Calls	Distributions	NAV
0	6.25%	1.20	0.00	1.20	6.25	0.00	7.50
1	12.50%	1.20	0.00	1.20	6.25	0.00	15.00
2	18.75%	1.20	0.00	1.20	6.25	0.00	22.50
3	25.00%	1.10	0.50	0.60	6.25	12.50	15.00
4	25.00%	1.00	0.50	0.50	0.00	0.00	12.50
5	50.00%	1.30	0.50	0.80	25.00	12.50	40.00
6	66.67%	1.35	0.50	0.85	16.67	8.33	56.67
7	75.00%	1.40	0.80	0.60	8.33	26.67	45.00
8	95.00%	1.40	0.80	0.60	20.00	16.00	57.00
9	100.00%	1.40	1.20	0.20	5.00	44.00	20.00
10	100.00%	1.40	1.20	0.20	0.00	0.00	20.00
11	100.00%	1.50	1.20	0.30	0.00	0.00	30.00
12	100.00%	1.60	1.20	0.40	0.00	0.00	40.00
13	100.00%	1.40	1.20	0.20	0.00	0.00	20.00
14	100.00%	1.40	1.40	0.00	0.00	20.00	0.00
15	100.00%	1.40	1.40	0.00	0.00	0.00	0.00
16	100.00%	1.40	1.40	0.00	0.00	0.00	0.00

Table IA3: Tabulates the quarterly cash-flow and NAV imputation for an example fund of size $100 with 16 quarters of data. This table assumes that calls, distributions, and NAVs are missing but imputed using the observed performance metrics.

Table IA4: Example Estimated Number of Limited Partners in a Fund

Observed						Estimation				Final
F	L^N	$\sum_{j=1}^{j=L^N} c_j$	$\%$	L^K	$a(L^N)$	$\tilde{F}$	$\tilde{F}$ vs. F	L^M	c_k	# LPs
100	5	100	*100%*	0	20.00	100.00	$\geq$	0	-	5
100	5	75	*75%*	2	25.00	125.00	$\geq$	0	12.50	7
100	5	65	*65%*	2	21.67	108.33	$\geq$	0	17.50	7
100	5	50	*50%*	2	16.67	83.33	$<$	1	16.67	8
100	5	25	*25%*	2	8.33	41.67	$<$	7	8.33	14
100	5	10	*10%*	2	3.33	16.67	$<$	25	3.33	32
100	5	5	*5%*	2	1.67	8.33	$<$	55	1.67	62
100	5	1	*1%*	2	0.33	1.67	$<$	295	0.33	302

Table IA4: Tabulates the estimated number of Limited Partners in a fund under various possible observed characteristics. F denotes fund size, c_j denotes the observed commitment made by LP j, $a(L^N)$ denotes the average observed commitment amount, $\tilde{F}$ denotes fund size estimated without adding any missing LPs and using $a(L^N)$, L^M denotes the estimated missing LPs, and c_k denotes the level of missing commitments for all LPs where commitments are missing $(L^M + L_K)$. Refer to section B for further variable descriptions.

Table IA5: Correlations Between Simulated and Imputed LP Profiles

	HHI^{Acutal}	$HHI^{Known\ Data}$	$HHI^{Imputed}$	$\#\ LPs^{Actual}$	$\#\ LPs^{Known\ Data}$
HHI^{Acutal}	1.00				
$HHI^{Known\ Data}$	0.12	1.00			
$HHI^{Imputed}$	**0.95**	0.16	1.00		
$\#\ LPs^{Actual}$	-0.61	-0.24	-0.62	1.00	
$\#\ LPs^{Known\ Data}$	-0.40	0.39	-0.40	0.59	1.00
$\#\ LPs^{Estimated}$	-0.60	-0.25	-0.62	**0.99**	0.58

Table IA5: Tabulates correlations between LP counts and commitment dispersions for a randomly created sample of funds following section B. Bold correlation coefficients denote the outcomes of our imputation procedure.

Table IA6: Fundraising Determinants

	𝟙(First Capital Call for Follow-on This Quarter)					
	(1)	(2)	(3)	(4)	(5)	(6)
Distribution/Fund Size	0.043**		0.042**			
	(2.38)		(2.21)			
Benchmark Return		-0.010	-0.006			
		(-0.51)	(-0.30)			
DPI				-0.003		-0.011**
				(-1.06)		(-2.01)
Cumul. Benchmark Return					-0.003	-0.010**
					(-0.67)	(-2.15)
Constant	0.037***	0.033***	0.038***	0.038***	0.035***	0.044***
	(9.35)	(9.36)	(9.48)	(9.53)	(7.07)	(7.59)
Controls	x	x	x	x	x	x
Fund FE			x			x
Adj. R^2	0.004	0.002	-0.020	0.003	0.002	-0.020
N	12,959	13,970	12,959	13,232	13,970	13,232

Table IA6: Regresses an indicator of whether a manager raised a follow-on fund in a given quarter on fund cash flows and market performance. The unit of observation is fund-quarter. Controls include the number of quarters elapsed since the fund's first capital call. The benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. Cumulative benchmark returns are calculated starting in the quarter of the fund's first capital call. Standard errors are clustered at the year-quarter level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA7: Alternate Difference-in-Differences Estimators

	(1) IRR	(2) TVPI	(3) PME	(4) DPI	(5) RVPI
DiD	-0.078***	0.244***	0.230***	0.270***	-0.025
	(-2.90)	(3.92)	(4.31)	(5.60)	(-0.57)
N	16,968	18,103	18,100	18,100	18,100
TWFE	-0.031	0.265***	0.182***	0.255***	0.010
	(-1.19)	(4.62)	(3.81)	(4.86)	(0.23)
N	16,968	18,103	18,100	18,100	18,100
Stacked	-0.042***	0.265***	0.180***	0.280***	-0.014
	(-5.11)	(11.50)	(8.71)	(12.64)	(-0.83)
N	77,518	82,953	82,900	82,900	82,900

Table IA7: Reports difference-in-differences estimates of the effect of a successful fundraising on key performance metrics using different difference-in-differences estimators. "DiD" implements a regression of the form:

$$y_{it} = \beta_1(\text{Post}_{it} \times \text{Treated}_i) + \gamma' X_{it} + \epsilon_{it},$$

where β_1 is the coefficient of interest, y_{it} is the quarterly performance metric of fund i in quarter t, Post indicates the sponsor of the fund successfully raised capital for a follow-on fund, Treated indicates the quarterly performance report occurred on or after the fundraising quarter, and X_{it} is a vector of controls. "TWFE" implements the same regression form but additionally includes fund and year-quarter fixed effects. "Stacked" implements the Cengiz, Dube, Lindner, and Zipperer (2019) stacked DiD estimator that only allows for comparisons within treatment cohorts. For example, all funds with a fundraising quarter of 2015Q1 would form one cohort. All specifications (except for "DiD") include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA8: Alternate Controls

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\tau}$ IRR	-0.047***	-0.047***	-0.046***	-0.016***	-0.014***	-0.065***
	(-2.61)	(-3.60)	(-2.80)	(-2.93)	(-2.63)	(-4.07)
Year-Qtr. FE	x	x	x	x	x	x
Fund FE	x	x	x	x	x	x
Lag PME		x				
Lag NAV		x	x		x	x
Lag DPI			x			
Lag IRR				x	x	
Lag TVPI						x
N	17,017	16,968	16,968	16,559	16,555	16,968

Table IA8: Tabulates the effect of a successful fundraising on IRRs, under different sets of controls, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. All calculations use fund and calendar time fixed effects. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA9: Alternate Weighting Schemes

Weight:	(1) Fund Size	(2) % Called	(3) # Est. LPs
$\hat{\tau}$ IRR	-0.031*	-0.051***	-0.041***
	(-1.89)	(-3.77)	(-2.72)
Year-Qtr. FE	x	x	x
Fund FE	x	x	x
Lag PME	x	x	x
Lag NAV	x	x	x
N	16,968	16,968	16,968

Table IA9: Tabulates the effect of a successful fundraising on IRRs, under different weighting schemes, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. The main results report equally-weighted estimates of the treatment effect. In contrast, these results are value weighted by other variables. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA10: Alternate Fundraising Dates

Shift:	(1) 1 Qtr.	(2) 2 Qtrs.	(3) 3 Qtrs.	(4) 4 Qtrs.	(5) 5 Qtrs.
$\hat{\tau}$ IRR	-0.046***	-0.041***	-0.035**	-0.034*	-0.028
	(-3.22)	(-2.68)	(-2.14)	(-1.93)	(-1.50)
Year-Qtr. FE	x	x	x	x	x
Fund FE	x	x	x	x	x
Lag PME	x	x	x	x	x
Lag NAV	x	x	x	x	x
N	16,968	16,709	16,564	16,191	15,618

Table IA10: Tabulates the effect of a successful fundraising on IRRs, after shifting the fundraising date by a fixed number of quarters, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. For example, if a fund has a fundraising date of 2015Q1, shifting the fundraising date by 1 quarter would calculate the treatment effect as if the fundraising quarter was 2014Q4. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA11: Annual Panels

	(1) IRR	(2) TVPI	(3) PME	(4) DPI	(5) RVPI
	Only Q1 Observations				
$\hat{\tau}$	-0.050***	0.033	-0.000	0.153***	-0.120***
	(-3.53)	(1.21)	(-0.03)	(4.11)	(-4.56)
N	4,084	4,371	4,370	4,370	4,370
	Only Q2 Observations				
$\hat{\tau}$	-0.046***	0.080*	0.036	0.176***	-0.097***
	(-3.38)	(1.86)	(1.11)	(4.46)	(-3.37)
N	4,310	4,606	4,604	4,604	4,604
	Only Q3 Observations				
$\hat{\tau}$	-0.043***	0.052**	0.008	0.188***	-0.135***
	(-3.40)	(1.99)	(0.70)	(5.15)	(-5.11)
N	4,370	4,684	4,684	4,684	4,684
	Only Q4 Observations				
$\hat{\tau}$	-0.048***	0.044	-0.003	0.153***	-0.109***
	(-2.79)	(1.30)	(-0.13)	(4.12)	(-4.11)
N	4,044	4,295	4,295	4,295	4,295

Table IA11: Tabulates the effect of a successful fundraising on IRRs as if variables are only viewed once per year rather than once per quarter. For example, the "*Only Q1 Observations*" component of the table displays results as if the data from the first quarter (Q1) of a given calendar-year represents all data for each fund in that calendar-year. In effect, this test also stretches fundraising events out over several quarters. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA12: Alternate Sample Restrictions

	(1)	(2)	(3)	(4)	(5)
Sample Period:	Qtrs. 4+	Qtrs. 8+	Qtrs. $\leq$ 40	Qtrs. 8-40	Fundraising $\pm$ 20 Qtrs.
$\hat{\tau}$ IRR	-0.047***	-0.041***	-0.033**	-0.028**	-0.028**
	(-3.60)	(-3.69)	(-2.53)	(-2.54)	(-2.42)
Year-Qtr. FE	x	x	x	x	x
Fund FE	x	x	x	x	x
Lag PME	x	x	x	x	x
Lag NAV	x	x	x	x	x
N	16,966	15,951	14,159	13,142	13,960

Table IA12: Tabulates the effect of a successful fundraising on IRRs, after restricting the sample to only include select observations relative to the first capital call or fundraising date, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. Column 5 retains all observations for failed fundraisers. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA13: Alternate Time Periods

Vintage Year:	(1) < 2006	(2) 2006+	(3) 2006-2009	(4) 2009+
$\hat{\tau}$ IRR	-0.043***	-0.028*	-0.021	-0.059***
	(-2.64)	(-1.89)	(-1.13)	(-2.85)
Year-Qtr. FE	x	x	x	x
Fund FE	x	x	x	x
Lag PME	x	x	x	x
Lag NAV	x	x	x	x
N	5,450	11,518	8,094	3,896

Table IA13: Tabulates the effect of a successful fundraising on IRRs, after restricting the sample to only include select vintage years, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA14: Alternate Weights for Failed Fundraisers

	(1) IRR	(2) TVPI	(3) PME	(4) DPI	(5) RVPI
Panel A: Oversample to 60%					
$\hat{\tau}$	-0.036***	0.224***	0.149***	0.239***	-0.015
	(-3.51)	(9.92)	(8.20)	(11.17)	(-1.00)
N	26,372	28,156	28,151	28,151	28,151
Panel B: Oversample to 70%					
$\hat{\tau}$	-0.030***	0.192***	0.126***	0.194***	-0.002
	(-2.70)	(7.40)	(6.01)	(7.95)	(-0.14)
N	22,323	23,856	23,852	23,852	23,852
Panel C: Oversample to 80%					
$\hat{\tau}$	-0.058***	0.153***	0.090***	0.228***	-0.075***
	(-5.22)	(5.04)	(3.80)	(8.31)	(-3.81)
N	19,742	21,077	21,073	21,073	21,073

Table IA14: Tabulates the effect of a successful fundraising on quarterly performance metrics, after over-weighting the failed fundraisers, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. For example, in the 60% panel, failed fundraisers are resampled (with replacement) until the fundraising success rate for all funds in the panel equals 60%. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA15: Alternate Data Provider: Preqin Cash Flows

		Placebo Tests		
	Baseline	Random Treatment	Random Timing	Random Treatment + Timing
	(1)	(2)	(3)	(4)
$\hat{\tau}$ IRR	-0.060***	0.023	-0.020	-0.022
	(-3.16)	(0.64)	(-0.93)	(-1.39)
Year-Qtr. FE	x	x	x	x
Fund FE	x	x	x	x
Lag PME	x	x	x	x
Lag NAV	x	x	x	x
N	9,096	5,155	5,970	7,229

Table IA15: Tabulates the effect of fundraising on reported quarterly IRRs using the fund-quarter cash-flow panel provided by Preqin rather than the fund-quarter performance panel provided by Cambridge Associates. Difference-in-Difference estimates are calculated using the Borusyak, Jaravel, and Spiess (2021) estimator. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA16: Alternate Attribution Orders

Remove All Except For:	(1) Quick Flips	(2) Delay Mark-Downs	(3) Grand-standing	(4) Delay Carry	(5) NAV Bias
$\hat{\tau}$ IRR	-0.042***	-0.023*	-0.036**	-0.031**	-0.013
	(-2.68)	(-1.76)	(-2.56)	(-2.07)	(-0.65)
Year-Qtr. FE	x	x	x	x	x
Fund FE	x	x	x	x	x
Lag PME	x	x	x	x	x
Lag NAV	x	x	x	x	x
Carry Def.	x	x	x		x
N	6,070	7,570	6,098	5,225	6,368

Table IA16: Tabulates the effect of fundraising on reported quarterly performance metrics after removing funds consistent with all window dressing techniques except for the manipulation technique denoted in the column header. For example, the column titled "Quick Flips" accounts for manipulation techniques listed in other columns, but not the quick flips technique. Difference-in-Difference estimates are calculated using the Borusyak, Jaravel, and Spiess (2021) estimator. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA17: Alternate Investor Performance Sensitivity Measurements

Investor Performance Sensitivity Measure	Ratio of Commitments to AUM		Ratio of Commitments to AUM in Alt. Assets		Ratio of Commitments to Target AUM in RE Assets		Ratio of Commitments to AUM in Private RE Assets	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median	-0.066***	0.001	-0.066***	-0.003	-0.071***	0.009	-0.058***	0.001
	(-4.17)	(0.04)	(-3.98)	(-0.14)	(-4.53)	(0.37)	(-3.35)	(0.04)
N	7,078	7,063	7,030	7,031	6,711	6,898	6,813	6,723
Value-Weighted	-0.061***	-0.015	-0.049***	-0.034*	-0.100***	-0.016	-0.056***	-0.032
	(-4.00)	(-0.77)	(-2.67)	(-1.93)	(-5.33)	(-0.53)	(-4.69)	(-1.13)
N	6,609	6,970	2,178	2,145	1,378	1,323	1,310	1,327
Panel AUM	-0.040**	-0.028	-0.046**	-0.027	-0.040**	-0.032*	-0.046***	-0.023
	(-2.39)	(-1.53)	(-2.54)	(-1.59)	(-2.24)	(-1.91)	(-2.80)	(-1.30)
N	5,692	6,136	5,054	5,410	5,611	6,042	4,947	5,577
Known LPs	-0.064***	-0.012	-0.056***	-0.025	-0.063***	-0.002	-0.052***	0.000
	(-4.15)	(-0.65)	(-3.63)	(-1.47)	(-4.05)	(-0.11)	(-3.11)	(0.01)
N	7,016	7,125	7,002	7,059	6,800	6,809	6,757	6,812
Known Commits	-0.052***	-0.016	-0.028	-0.036*	-0.051***	0.004	-0.052***	0.006
	(-3.43)	(-0.78)	(-1.42)	(-1.95)	(-3.43)	(0.17)	(-3.54)	(0.21)
N	6,773	7,368	6,632	6,808	5,688	6,461	5,523	5,742

All specifications include: fund FE, calendar time FE, and controls

Table IA17: Reports difference-in-differences estimates of the effect of a successful fundraising on reported net IRRs after splitting the sample by measures of investor performance sensitivity to fund returns using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Row titles indicate inputs to the investor sensitivity formula. "Median" indicates that funds are sorted based on the median investor elasticity of each fund. "Value-Weighted" indicates that funds are sorted based on the value-weighted investor elasticity of each fund. "Panel AUM" indicates that elasticities are calculated using only the actuarial assets (per GASB) of public pension funds as of the commitment year. "Known LPs" indicates that no imputations were made for the LP count in constructing sensitivity measures. "Known Commits" indicates that no imputations were made for the commitment levels in constructing sensitivity measures. "High" indicates the sensitivity measure is above the sample median and "Low" indicates the sensitivity measure is below the sample median. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA18: Additional Alternate Investor Performance Sensitivity Measurements

	Prev. 3 Commitments		Prev. 5 Commitments		Prev. 10 Commitments	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\tau}$ IRR	-0.038*	-0.033**	-0.052***	-0.015	-0.057***	-0.012
	(-1.78)	(-2.17)	(-2.99)	(-0.78)	(-3.33)	(-0.63)
N	7,177	6,964	7,220	6,921	7,201	6,940

Table IA18: Reports difference-in-differences estimates of the effect of a successful fundraising on reported net IRRs after splitting the sample by measures of investor performance sensitivity to fund returns using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Investor performance sensitivity at the fund level (i) is calculated as:

$$\text{Investor Performance Sensitivity}_i = \frac{1}{J} \sum_{j \leq J} \frac{c_{ij}}{\bar{c_j}},$$

where J denotes the number of known investors in the fund, c_{ij} is the commitment made by each LP (often imputed), and $\bar{c_j}$ is calculated as the rolling average level of commitments to other PERE funds made by LP j. The column headers denote the previous number of commitments used in the rolling average. For example, "3" indicates that the commitment to fund i (c_{ij}) and the previous two commitments to PERE funds are used in the calculation. "High" indicates the sensitivity measure is above the sample median and "Low" indicates the sensitivity measure is below the sample median. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA19: Alternate Sample Summary Statistics

	Nobs.	Mean	Std. Dev	25%	50%	75%
			Panel A: Venture Capital			
Qtrly. IRR	9402	0.05	0.20	-0.05	0.05	0.14
Qtrly. PME	9949	1.03	0.43	0.79	0.97	1.22
Fund Size ($MM)	238	362.76	319.42	164.55	300.00	483.25
Final IRR	247	0.05	0.21	-0.01	0.07	0.16
Final PME	247	1.00	0.63	0.56	0.96	1.35
			Panel B: Buyout			
Qtrly. IRR	28286	0.07	0.18	0.01	0.09	0.16
Qtrly. PME	30315	1.06	0.34	0.87	1.03	1.21
Fund Size ($MM)	755	1474.85	2552.33	240.40	600.00	1345.00
Final IRR	770	0.10	0.15	0.06	0.12	0.17
Final PME	770	1.08	0.43	0.86	1.08	1.30
			Panel C: PERE			
Qtrly. IRR	6013	0.08	0.18	0.02	0.10	0.17
Qtrly. PME	6554	0.98	0.26	0.86	0.99	1.12
Fund Size ($MM)	196	1008.55	1613.67	250.00	530.00	918.95
Final IRR	198	0.07	0.16	0.04	0.11	0.15
Final PME	198	0.93	0.34	0.78	0.99	1.12

Table IA19: Tabulates summary statistics by asset class for the funds in our alternate sample containing additional asset classes. Vintage years include 2001 through 2014. Panel observation years include 2006 through 2019. PME are the Brown, Gredil, and Kaplan (2019) interim PME calculated using the S&P 500 index. Final performance metrics are calculated at the latest of the last reported quarter before 2019 or the last quarter in which Net Asset Values exceed zero.

Table IA20: Window Dressing in an Alternate Sample Within Alternate Asset Classes

	(1) IRR	(2) TVPI	(3) PME	(4) DPI	(5) RVPI
Venture $\hat{\tau}$	-0.135***	0.116***	0.025*	0.147***	-0.030
	(-5.52)	(4.05)	(1.69)	(4.21)	(-1.51)
N	9,327	9,674	9,674	9,674	9,674
Buyout $\hat{\tau}$	-0.068***	0.118***	0.040*	0.138***	-0.020
	(-4.83)	(4.07)	(1.94)	(4.10)	(-1.21)
N	28,096	29,417	29,417	29,417	29,417
PERE $\hat{\tau}$	-0.046**	-0.010	0.026	0.144***	-0.154**
	(-2.30)	(-0.35)	(1.28)	(2.58)	(-2.50)
N	5,962	6,309	6,309	6,309	6,309

Table IA20: Tabulates difference-in-differences estimates of the effect of a successful fundraising on key performance metrics using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. These results use the fund-quarter cash-flow panel provided by Preqin for sub-samples of funds in different asset classes. All specifications include fund and calendar time fixed effects and controls for lagged PME and lagged NAV. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.