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 boost and smooth their funds' returns if doing so has a larger effect on their 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 boosted and smoothed interim returns due to agency frictions within their organizations.

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Return manipulation in delegated asset management is often thought to involve actions taken by fund managers in attempts to mislead investors. Private Equity (PE) is an increasingly important class of delegated asset management where it is frequently contended that fund managers manipulate reported returns. Regulators have argued that PE fund managers (General Partners; GPs) mislead PE investors (Limited Partners; LPs) about performance, and studies have found evidence of return manipulation, especially when some PE fund managers are marketing funds to potential investors.[1]

In this paper, we propose a novel catering explanation for PE return manipulation that contrasts with traditional characterizations of performance misrepresentation. We show that GPs boost and smooth interim performance reports to cater to their LPs' "demand" for manipulated returns, similar to the idea that firms issue dividends to cater to investor demand for dividend payments (e.g., Baker and Wurgler (2004)) or that banks design financial products to cater to yield-seeking investors (e.g., Célérier and Vallée (2017)). Our catering results have a simple explanation: some PE investors face agency frictions within their LP organizations that make boosted and smoothed returns attractive.

The following quote contextualizes our main ideas.

> *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. – Bob Maynard (2015), the Chief Investment Officer of Idaho's Public Employee Retirement System at a CalPERS Private Equity Workshop.*

We think of this "phony happiness" as highlighting the incentives for PE GPs to manipulate their returns to cater to their LPs. PE GPs can manipulate their returns by boosting the quarterly Internal Rates of Return (IRRs) reported to their LPs – calculated using valuations of illiquid, non-traded assets and interim cash flows. GPs can boost IRRs by, for example, strategically timing asset acquisitions and dispositions or by misstating fund net asset values (NAVs). Maynard (2015) mentions another way GPs can manipulate the returns reported to LPs which involves a specific

[1]The U.S. Security and Exchange Commission recently investigated PE reporting practices and fees (see https://on.wsj.com/3Jnr3PU). Barber and Yasuda (2017) and Brown, Gredil, and Kaplan (2019), for example, are two recent studies that primarily analyze fund net asset value exaggeration in PE, which is one of the several return manipulation strategies we consider.

type of NAV misstatement: smoothing quarterly NAVs.

The outcomes of boosting and smoothing can be attractive to LP investment managers. Boosted IRRs allow LP investment managers to report higher headline returns. Smoothed NAVs enable LP investment managers to report artificially lower correlations between their fund returns and the returns of publicly traded assets, leading to artificially higher Sharpe ratios and alphas.[2] Chief Investment Officers (CIOs) and trustees of public pension plan LPs often face shorter investment horizons than their principals (such as taxpayers and pension beneficiaries) due to, for example, political constraints and career concerns, and may benefit from boosted and smoothed returns. If a GP boosts IRRs and smooths NAVs, LP investment managers who have invested in the GP's fund may improve their internal job security or other labor market outcomes. The LP investment managers may also improve the reported funding status of their pension plan, increase their performance-based compensation, or insulate themselves from temporary dislocations in public market prices. However, while manipulated returns can benefit individual LP investment managers, they can also distort allocations away from a more optimal risk-return strategy for their longer-horizon principals. This can have potentially harmful and non-trivial real effects.

Our study focuses on if a GP's decisions to boost IRRs and smooth NAVs are driven by whether doing so caters to its LPs. We use a large sample of private equity commercial real estate (PERE) funds and investors spanning 2001 to 2019 to test this hypothesis. One reason PERE funds are attractive for testing our catering hypothesis, relative to, for example, buyout or venture funds, is that they have consistently underperformed various public market indices, with estimates of average underperformance equaling 300 to 400 basis points (bps) per year (e.g., Gupta and Van Nieuwerburgh (2021), Riddiough (2022), and Li and Riddiough (2023)), but still have grown to be the second-largest PE asset class by commitments and a primary method of real estate investing for institutional allocators. The high demand for underperforming PERE funds continues despite alternative ways to gain commercial real estate exposure, such as publicly listed

[2]Several others have also argued that PE investors might prefer smoothed returns. 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 could be negative to reflect the "convenience" of illiquidity for public pension PE investors. Cochrane (2022) argues that PE investments are attractive to investors, in part because they are hard to mark-to-market. Riddiough (2022) argues that U.S. public pensions accept a return discount to access a "veil of illiquidity" from investing in commercial real estate through PE funds rather than listed real estate. Cliff Asness refers to return smoothing as "volatility laundering." (See https://bit.ly/3HIFm1M.) Korteweg and Westerfield (2022) offer a similar synthesis.

real estate investment trusts. For example, U.S. public pensions allocate $4 to PERE funds for every $1 invested in publicly listed real estate - a ratio that has increased about 30× over the past two decades (Beath and Flynn 2018).

In our analysis, our primary measure of a GP's catering incentives is the average effect of a PERE fund's returns on its LPs' portfolio returns, calculated as the average weight of a fund in its' LPs' portfolios. This measure captures the extent to which a GP may find it optimal to boost IRRs or smooth NAVs to benefit its LPs: manipulating reported returns is more likely to be a positive NPV project for a GP if doing so has a larger impact on their LPs' returns. For example, if the GPs of a fund on average manage 4% of their LPs' assets (roughly the 75th percentile in our sample), the returns the fund reports – and any boosting or smoothing embedded in these reported returns – are roughly 8× more impactful for its investors than if the GPs of the fund oversee only 0.5% of their LPs' assets (roughly the 25th percentile in our sample). This intuition is similar to strategies employed by, for example, Bergstresser, Desai, and Rauh (2006).

Our first set of tests examines if higher catering incentives predict whether GPs boost IRRs. We use variation in GP boosting incentives due to fundraising events to measure IRR boosts of potentially long durations. Fundraising events are discrete points in funds' lives that "shock" GP incentives to boost IRRs: GPs have an incentive to report boosted IRRs for fund #N while raising capital for fund #N+1, but this incentive decreases after completing fundraising for fund #N+1. Based on our catering hypothesis, the motivation to raise capital for a follow-on fund with boosted IRRs should be higher among funds with higher catering incentives. We relate IRR boosts to catering incentives by estimating a staggered difference-in-differences (DiD) specification to approximate the differential effects of fundraising on reported IRRs separately for subsets of funds with high- and low-catering incentives.[3]

Our difference-in-differences estimates demonstrate that GP catering incentives (the average weight of a fund in its' LPs' portfolios) predict IRR boosting: headline IRR boosts average 640 bps among funds that face stronger catering incentives, but an insignificant 110 bps among funds that face weaker catering incentives. We also find that the IRR boosts are long-lived and per-

[3] We also address numerous potential econometric and identification concerns by, for example, using a heterogeneity robust DiD estimator, providing evidence that factors that likely affect reported IRRs only through their effects on fundraise timing explain empirical patterns in fundraising, using alternative approaches that do not rely on fundraising events to identify shocks to manipulation incentives, and conducting a battery of falsification and robustness tests.

sistent - remaining in the IRRs that GPs with higher catering incentives report to their LPs beyond the fundraising window. Additional analysis indicates that IRR boosts noticeably distort reported investor-level IRRs for LPs of funds with higher GP catering incentives, do not harm GPs' ability to raise capital from LPs, and are accomplished primarily by altering the timing of cash flows rather than exaggerating reported fund NAVs.

We next examine whether GP catering incentives predict "smoothness" in reported fund NAVs – a specific type of NAV manipulation not reliant on overstating NAVs and identified without fundraising events. Regressions of quarterly NAV returns on lagged and contemporaneous public market returns indicate that about 33% of public market returns pass through to fund NAV returns within a given year. However, only about 40% of this pass-through occurs in a contemporaneous quarter; the remaining 60% comes from public market returns lagged by 1-, 2-, and 3-quarters. We find that this tendency for GPs to insulate LPs from contemporaneous market returns is more pronounced among GPs facing high catering incentives than among GPs facing low catering incentives. Additional time series and panel tests are consistent with smooth returns being attractive to LPs.

Our remaining tests examine the source of a GP's catering incentives. We posit that boosted IRRs and smoothed NAVs are more likely to cater to LP investment managers if the LP investment managers face stronger agency frictions within their LP organizations. To examine this agency hypothesis, we conduct analyses at the LP commitment level, testing if indicators of agency frictions within LP organizations predict whether LP investment managers make larger commitments (as a fraction of their assets) to a given PERE fund – which, in doing so, increases the catering incentives for the GPs of the fund.

We focus our agency tests on commitments made by public pension LPs. Our primary measure of agency frictions is the degree of political representation on a pension's board of trustees, measured as the fraction of board trustees who are politically appointed – a fraction that is relatively stable over time. Andonov, Hochberg, and Rauh (2018) find that PE investment decisions made by politically appointed trustees are related to political expediency and political contributions from the finance industry, resulting in underperformance on PERE investments in a way that appears unrelated to the financial expertise of the trustees.

Cross-sectional regressions controlling for the state of the pension, a LP's previous commitments, time trends, and other potential commitment determinants support our agency hypothesis. Pension boards characterized by a higher degree of political representation tend to make larger commitments (as a percent of pension assets) to a given PERE fund, increasing the catering incentives of their GPs. We find similar results using other measures of agency frictions: poorly-funded pensions, smaller pensions, and pensions that compensate their CIOs at lower levels all tend to make commitments that increase the catering incentives of their GPs. In addition, panel regressions using variation in public pension trustee politicization to identify shifts in GP catering incentives (rather than fundraising events and the weight of funds in LPs' portfolios) also support our agency hypothesis; the level and smoothness of NAV returns both positively covary with the political representation of a PERE fund's public pension LP trustees in the same year.

We also examine other economic characterizations of return manipulation related to, for example, deception and GP reputation, where PERE GPs with higher catering incentives are more likely to boost returns and mask risk in a way responding to other features of the GP-LP relationship rather than as a response to agency frictions in their LPs' organizations. These alternative frameworks, however, have limited support in our data. Complementary tests explicitly considering these other mechanisms further support our mechanism where GPs boost and smooth returns to cater to agency-driven LP demand for manipulated returns.

Our results contribute to the literature that studies return manipulation in delegated asset management (e.g., Chevalier and Ellison (1997), Bollen and Pool (2009), and Agarwal, Gay, and Ling (2014)). We provide a novel catering explanation for IRR boosting and NAV smoothing, which complements studies examining the degrees of return boosting and smoothing among PE funds (e.g., Gompers (1996), Phalippou (2008), Jenkinson, Sousa, and Stucke (2013), Lopez-de-Silanes, Phalippou, and Gottschalg (2015), Barber and Yasuda (2017), Chakraborty and Ewens (2018), Brown, Gredil, and Kaplan (2019), Hüther (2021), Brown, Ghysels, and Gredil (2023), and Pham, Turner, and Zein (2023)). More generally, our results add to the evidence of managerial catering to investors (e.g., Baker and Wurgler (2004), Baker, Greenwood, and Wurgler (2009), Gennaioli, Shleifer, and Vishny (2012), Harris, Hartzmark, and Solomon (2015), and Célérier and Vallée (2017)), in our case PE investors.

Our work also contributes to recent literature examining public pensions' increasing allocations to alternative assets rather than publicly traded assets. Explanations for alternative asset allocations at the public pension level include, for example, extrapolative expectations (Andonov and Rauh 2021) and consultant- and peer-driven beliefs (Begenau, Liang, and Siriwardane 2023). We highlight an agency-based catering framework that helps explain public pensions' preferences for insulation and return boosting available in PERE but not in listed real estate. In doing so, we also contribute to studies of agency conflicts between PE GPs and LPs (e.g., Robinson and Sensoy (2013) and Gahng and Jackson (2023)) and studies of conflicts in public pension investment structures (e.g., Andonov, Bauer, and Cremers (2017), Andonov et al. (2018), and Dyck, Manoel, and Morse (2021)). The novel aspect of our work is our focus on how agency frictions within investor organizations create incentives for GPs to boost IRRs and mask risk.

1 Data, Sample Construction, and Summary Statistics

As background, PE investing occurs primarily through PE funds. Funds are typically closed-end, limited life, limited partnerships, often lasting 8-12 years. PE firms sponsor the funds as general partners. Institutional investors (e.g., pension funds) and high net-worth individuals serve as LPs, contribute most of the capital, and in return, receive net-of-fee proceeds resulting from investments made by GPs. GPs typically embark on fundraising campaigns every few years, beginning the process before the current fund expires and its actual performance is realized.

We obtain data on the quarterly performance of PERE funds from Cambridge Associates (CA). CA is one of the largest providers of investment consulting services for PE investors. CA obtains fund performance data directly from the quarterly reports provided by GPs to their LPs, sourcing these reports from their clients, regular meetings with GPs, and relationships with PE industry associations, such as the Institutional Limited Partners Association (ILPA). CA does not use Freedom of Information Act (FOIA) requests, regulatory filings, manager surveys, or press scrapings to obtain data (Cambridge Associates 2023). Brown, Harris, Jenkinson, Kaplan, and Robinson (2015) further discuss CA data sourcing. Compared to other PE datasets, CA data display similar trends and levels in performance across vintages (Harris, Jenkinson, and Kaplan 2014).

Our CA dataset includes annualized Internal Rates of Return (IRR), Total Value to Paid-in Capital (TVPI), Distributions to Paid-in Capital (DPI), and quartiles of percent called at a quarterly frequency for 910 PERE funds active in the period 2006 to 2019. CA censors the first year of a fund's reported IRRs, and we censor interim IRRs with absolute values exceeding 100%. 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 reported value of all remaining investments within a fund (NAVs), scaled by the value of called capital, as of a given quarter. All performance metrics are reported net of fees and are "to-date" measures, reflecting cumulative cash flows, NAVs, or both cumulative cash flows and NAVs as of a given quarter.

We include closed-end commercial real estate (CRE) PERE funds with at least 20 quarters of reported IRRs that follow an opportunistic, value-added, distressed, core, or core-plus strategy, have a vintage of 2001 or later, and do not primarily acquire land or operating companies in our analyses. We also require that funds report IRRs during the estimated fundraising quarter. Our resulting sample contains 448 funds managed by 208 PERE firms with vintages from 2001 - 2014.[4] We describe the composition of these funds in Table IA1.

Panel A of Table 1 describes our quarterly performance data. We calculate quarterly cash flows and NAVs using quarterly changes in DPI, RVPI, and percent called. Andonov, Kräussl, and Rauh (2021) employ a similar procedure, and we discuss and validate these calculations in Section IA.1. We calculate Brown et al. (2019) interim (to-date) Public Market Equivalents (PMEs) each quarter using the FTSE Nareit U.S. Equity real estate investment trust (REIT) index, which excludes mortgage REITs. Quarterly NAV returns (r_{it}^{NAV}) are winsorized at the 1% level and are calculated as: $\log(NAV_{it})$ - $\log(NAV_{i,t-1}$ - Cash Flow$_{it})$, where i indexes the fund and t indexes the year-quarter. "NAV bias" denotes quarterly NAV returns not explained by cash-flows or public market returns over the same quarter, following the naming convention used by Brown et al. (2019). We winsorize NAV bias at the 1% level, and calculate it as: $\log(NAV_{it})$ - $\log((1+r_t^b) \times NAV_{i,t-1}$ - Cash Flow$_{it})$, where r_t^b denotes the quarterly return of the U.S. Equity REITs index. Panel B of Table 1 indicates that after fees, the average last reported IRR across the sample is about 5%, and the average last calculated PME is 0.86 – similar to statistics reported for PERE funds by Andonov et al. (2021) and Gupta and Van Nieuwerburgh (2021).

We supplement the CA data with LP commitment data from Preqin. We merge the two datasets by manually identifying each fund and GP from the CA dataset in the Preqin universe.

[4] Similarly filtering cash flow data from Preqin results in a smaller sample of 271 CRE PERE funds managed by 160 PE firms. 48% of these Preqin funds are also in the larger CA sample.

Commitment-level data points include the LP name, investor class (e.g., public pension), and identifying information for the PERE fund receiving the LP capital commitment. Our sample includes 5,921 capital commitments from 1,374 LPs, which we further describe in Table IA1. The dollar value of each LP capital commitment is not always available. Panel B of Table 1 shows that, for the average fund in our sample, 22.76% of the dollar value of its capital commitments are available in our commitment data. For our main results using commitment data, we exclude 128 funds where less than 5% of the fund's capital commitments are available, raising the average commitment coverage to 31% in the resulting sub-sample of 320 funds. To exploit the richness of the commitment data (and avoid further excluding funds), our headline results estimate missing commitments by distributing the dollar value of missing fund commitments among other LPs in the fund, accounting for the fact that some LPs may be missing from the Preqin database. We discuss our imputation in Section IA.2 and provide a validating simulation. Additionally, we ensure our results are robust to only using observations where commitment data are available (i.e., not using our imputation) and adopting different weighting and distribution schemes for known commitments.

Using merged CA and Preqin data, we also determine whether each fund in our sample has a "follow-on fund." The follow-on fund assigned to each fund is the first closed-end CRE PERE fund raised by the same GP with a vintage year at least three years after the current fund's vintage year, following Brown et al. (2019). We look for follow-on funds in both the CA and the Preqin databases, addressing concerns that CA data may not contain all consecutive funds in a sequence. We complete our search across databases in September 2021, giving each GP in our sample at least seven years to raise capital for a follow-on fund. We identify a follow-on fund for 416 funds. We manually confirm the operating status for each of the 32 fund GPs without a follow-on fund, limiting potential false negatives. These fund managers generally went out of business, were acquired, or are still active but no longer manage PERE funds. False positives are unlikely in our classification. Instead, a concern is that our sample overrepresents successful fundraisers. We address this concern in our internet appendix by ensuring that our results are robust to oversampling unsuccessful fundraisers, effectively putting more weight on the failed fundraisers, and mitigating some of this bias, similar to weighting strategies employed by Chakraborty and Ewens (2018).

The "fundraising quarter" assigned to each fund is the quarter of the first capital call of the follow-on fund, following Barber and Yasuda (2017) and Brown et al. (2019). This definition requires interim performance data for the follow-on fund, which are not always available. Where these data are missing, we set the fundraising quarter as the median number of quarters it took for other successful fundraisers in the same vintage to call capital for a subsequent fund. Similar results attain if we drop funds with missing data or use different imputation methods (e.g., specific quarters within the vintage year of the follow-on fund listed in Preqin). In our internet appendix, we also show our results are robust to uniformly shifting the fundraising date up to four quarters earlier and to calculating results at an annual rather than a quarterly unit of observation, reflecting the facts that LPs may receive reports with a lag and that fundraising can last longer than a single quarter. Figure IA2 plots the time series of fundraising events in our sample. There are an average of 8.2 fundraising events and 309 funds reporting an IRR in a given quarter.

We also obtain additional data for U.S. defined benefit public pension LPs that committed capital to funds in our sample. First, we gather data from the Public Plans Database (PPD). The PPD collects comprehensive annual financial reports filed by 210 public pension funds in the United States, covering about 90% of state and local defined benefit pension assets and members in the U.S. from 2001 - 2020. For each pension fund, we manually identify the plan sponsor in Preqin and aggregate assets, liabilities, and other data points at the "system" level, reflecting the economics of allocation responsibilities.[5] Second, we retrieve data on the board of trustees of each pension plan, made available by Andonov et al. (2018). Board trustees represent individuals from the state, the pension plan, or the general public. Trustees are elected, ex officio, or appointed. In our tests using board composition data, we refer to the combined percentage of board members that are either state-appointed or state–ex officio as "state-political" because these two groups of trustees are either elected politicians or appointed by elected politicians, following Andonov et al. (2017) and Andonov et al. (2018).[6] Third, we retrieve compensation data (annual salaries and bonuses) for pension fund Chief Investment Officers (CIOs) for fiscal years 2001-2018, obtained through FOIA requests by Lu, Mullally, and Ray (2021). In this pool of CIOs, the average CIO

[5]We map the 210 pension funds in the PPD to 165 investing entities in Preqin. For example, we aggregate the Washington Law Enforcement & Firefighters Plan, Washington PERS, Washington School Employees Plan, and Washington Teacher's Plan from the PPD to the Washington State Investment Board in Preqin.

[6]We also correct eight of the commitments in our sample made by the Indiana Public Employees' Retirement Fund (PERF) and the Indiana Teachers' Retirement Fund (TRF) that were affected by their merger into the Indiana Public Retirement System. Three other public pension mergers occurred during our observation period but did not affect the labeling of any LPs in our sample. We have merging entities inherit the combined entity's trustee composition and other data following the merger. We thank Aleksandar Andonov for sharing these data.

has a six-year tenure and the median CIO has a four-year tenure.

These additional data are available for 110 U.S. defined benefit public pension LPs that made 1,080 commitments (with dollar values available in Preqin) to 255 PERE funds in our sample. Similar catering results attain using only these 255 PERE funds or only the set of funds where we do not have additional characteristics for a fund's public pension LPs (due to the fund not raising capital from public pensions or due to missing commitment dollar amounts). As of the commitment year (based on a match between pension fiscal years and fund vintage years), Panel C of Table 1 indicates that the average commitment equals 0.33% of pension assets (≈ $70 million), the average pension plan reports a funding ratio of 78.93%, and 30.58% of board trustees are either elected politicians or appointed by elected politicians (% State-political).

2 Measuring IRR Boosting

In this section, we examine whether GPs boost IRRs. GPs can boost IRRs by strategically timing asset acquisitions, dispositions, and markdowns.[7] They can also misstate fund NAVs. We use fundraising events to identify shifts in GP incentives to engage in these actions that boost IRRs. GPs face incentives to boost the IRRs of fund #N before raising capital for fund #N+1, but after raising capital for fund #N+1, their incentives to boost the returns of fund #N weaken. Figure 1 and Figure 2 plot the IRRs that GPs in our sample report to their LPs, indicating that reported IRRs tend to peak during fundraising events.

At the same point in time, different GPs face different incentives to boost IRRs, and at different points in time, the same GP faces different incentives to boost IRRs. This variation makes fundraising events attractive for identifying IRR boosting: they are staggered, discrete, and shock boosting incentives. In the context of our catering hypothesis, our main tests examine *which* funds raise capital for follow-on funds with boosted IRRs: the motivation should be higher among funds with higher catering incentives. To make use of fundraising shocks to boosting incentives, we estimate a staggered difference-in-differences (DiD) specification. Identifying variation comes

[7] Exiting investments early permanently increases the final IRR of the fund if the discount rate applied to the exited investments – to transfer cash flows from later exit times to earlier exit times– is lower than the IRR the fund would have achieved but for selling the properties earlier. Delaying capital calls can achieve a similar result (e.g., Albertus and Denes (2020)).

from comparing the reported IRRs among GPs that have raised a follow-on fund as of a given quarter (the "treated" group) to the reported IRRs of GPs that have not yet raised a follow-on fund in that same quarter (the "control" group).

Throughout, we use the Borusyak, Jaravel, and Spiess (2021) DiD "imputation" estimator to estimate the effect of fundraising on reported IRRs and visually inspect for pre-trends. This estimator is robust to treatment effect heterogeneity and avoids issues of spurious identification, contaminated fixed effects, and negative weights, unlike a two-way fixed effects OLS regression (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 year-quarter 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 ($\hat{\tau}$) 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 an equally-weighted average of imputed treatment effects; however, similar results attain using other weighting choices, such as percent called or fund size (Table IA7). In all specifications, we include fund fixed effects that allow for different baseline IRR outcomes across funds, and year-quarter fixed effects that accommodate overall trends in reported IRRs. We also include one quarter lags of the fund's to-date PMEs and fund 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 (Table IA8). In untabulated results, we additionally confirm our results are robust to using the Callaway and Sant'Anna (2021) DiD estimator, which imposes a different parallel trends assumption and is also robust to treatment effect heterogeneity with staggered treatment timing. We cluster standard errors at the fund level, allowing errors to be serially correlated within funds.

The identifying assumption in our DiD specification is parallel trends; reported IRRs–within a fund and conditional on the year-quarter of the report and lagged performance controls–

would follow the same trend but for whether GPs have raised capital for a follow-on fund as of a particular quarter. Event studies and robustness tests allow us to inspect for pre-trends and rule out several confounding or mechanical factors. The primary concern, however, is that GPs have discretion in fundraise timing. Reported IRRs may determine fundraise timing (reverse causality), and time-varying omitted variables might coincide with fundraising events (potentially determining fundraising outcomes and causing shifts in performance). We address this concern in detail in Section 2.1 after presenting a baseline treatment effect estimate. Also, as an additional way of testing the economics of our catering hypothesis, we provide evidence that complementary frameworks relying on variation in LP agency constraints (rather than fundraising events) to identify shocks to GP manipulation incentives result in similar catering conclusions (Section 3.4).

2.1 Fundraising and Reported IRRs

Table 2 reports the average effect of raising a follow-on fund on IRRs estimated from the DiD regression described in Section 2. Column (1) indicates that reported IRRs decline by 470 basis points as a result of *successfully* raising capital for a follow-on fund. This point estimate means that to-date IRRs after fundraising are 470 bps lower than counterfactual IRRs constructed using pre-fundraising observations, on average. For example, if the average to-date IRR is 5.3% after calling capital for a follow-on fund, this estimate implies that the counterfactual post-fundraising IRR is 10% based on pre-fundraising trends (after including fixed effects and controls). This estimate is statistically significant and economically meaningful; 470 bps equals roughly half of the median to-date IRR reported during fundraising.

Figure 3 plots dynamic DiD estimates of the effect of fundraising on reported IRRs.[8] The event-study plot shows no pre-trends and a monotonic decrease in reported IRRs relative to counterfactual IRRs after fundraising events, consistent with our parallel trends identifying assumption. We interpret these results as evidence that IRRs reported to LPs are, on average, boosted before and during fundraising. A battery of falsification, placebo, and other robustness tests in our internet appendix gives us further confidence in our result.

[8]Pre-trend coefficients are estimated following Borusyak et al. (2021) by regressing IRRs on event-time indicators accompanied by the full model of fixed effects and controls in the control sample of fund-quarter cells where the GP has not called capital for a follow-on fund. Our pre-trend plot only includes one year before fundraising because earlier IRRs tend to be less meaningful.

2.1.1 Reverse Causality

One potential concern with our interpretation is reverse causality: reported IRRs may determine fundraise timing. To assess this concern, we repeat our main tests using predicted rather than actual fundraising events. We construct predicted fundraising events assuming fundraising occurs; once a fixed number of years have elapsed in funds' lives, once the GP has called a fixed percentage of committed capital, or according to historical patterns in fundraising cycles. This set of predicted fundraising events captures the expiration of boilerplate fund terms in Limited Partnership Agreements (e.g., "successor fund provisions" that limit GP discretion in fundraise timing; Table IA4), the rule of thumb for LPs to ignore reported IRRs within the first few years, and industry norms around when GPs are expected to embark on fundraising campaigns, almost always within the first five years of a fund's life (likely sending a negative signal to potential investors if occurring much later). Our fixed effect specifications are also helpful in these tests, partialing out GP-specific fundraising capabilities and time-varying market conditions.

Unlike our estimated treatment effects of fundraising on IRRs using actual fundraising events, the estimated effects using predicted fundraising events are not directly affected by GP discretion. Actual fundraising also closely follows predicted fundraising, with 2/3 of funds in our sample raising a follow-on fund during years three to five (Figure IA3), consistent with industry norms affecting the timing of fundraising. These tests are in the spirit of a pseudo-instrumental variables design: we examine whether industry norms around when fundraising should occur, which should affect IRRs only through their effect on fundraise timing, generate similar variation in reported IRRs among funds where fundraising timing responds to industry norms. We present our results using predicted fundraising events in Table IA5, finding similar treatment effect estimates. These results help mitigate concerns about reverse causality: if the timing of fundraising events is anticipated, it is less likely that this timing is responding to variation in reported IRRs.

2.1.2 Boost Decomposition

Another potential concern with our interpretation is that time-varying omitted variables might coincide with fundraising events. To address this concern, we show that our treatment effect estimates are attributable to boosting behavior identified in previous literature. Specifically, the remaining columns in Table 2 decompose our baseline treatment effect estimate along several metrics related to potential boosting techniques. We remove funds that we flag as having altered the timing of cash flows to LPs or having strategically reported fund NAVs and re-estimate the effect of fundraising on reported IRRs within the resulting sub-samples (retaining all unsuccessful fundraisers in the sub-samples). The change in the estimated treatment effect relative to the baseline estimate of 470 bps implies the percentage of the estimated treatment effect attributable to funds flagged as having boosted IRRs according to a particular boosting flag. For example, a residual treatment effect (after removing a subset of funds) of −200 bps implies that approximately 57% of the headline treatment effect is attributable to the removed funds (≈ (470 bps − 200 bps)/470 bps). We discuss each technique below and provide a summary in Table A1.

Quick-Flips: "Quick-Flips" are akin to "selling winners and holding losers." We define funds that made quick-flip investments before fundraising events as those with (i) a DPI per year at the time of the fundraising quarter in the top tercile of all DPIs per year during fundraising quarters (measured in event time) and (ii) fund-quarters with $RVPI_{it} < .05$, where the fund is close to liquidated with few remaining unexited investments.[9] Condition (i) captures whether GPs sell winners before raising capital for a follow-on fund. Condition (ii) tests whether GPs hold their losers, i.e., whether underperformance of assets that remain in the fund towards the end of its life underpin estimated treatment effects. Phalippou (2008) and Lopez-de-Silanes et al. (2015) discuss the quick flips strategy.

Grandstanding: "Grandstanding" is similar to making quick flip investments: GPs might exit their best investments before fundraising to boost reported IRRs. Gompers (1996) provides evidence of grandstanding among young venture capital funds. We flag a fund as 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.[10] Incidences of the grandstanding flag are positively

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

[10]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 a DPI of 1.1 one year prior, its grandstanding value would be 9.1%. We would be less likely to flag the second 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.

correlated with incidences of the quick-flips flag.

Delay Markdowns: GPs might also boost interim IRRs by waiting to mark down underperforming investments until after raising a follow-on fund. Barber and Yasuda (2017) and Chakraborty and Ewens (2018) provide evidence that markdowns increase after fundraising events. We measure markdowns following Barber and Yasuda (2017) as: $\text{Markdown}_{it} = \min(\text{NAV}_{it} - \text{NAV}_{i,t-1} + (\text{Distributions}_{it} - \text{Calls}_{it}), 0)/\text{Fund Size}_i$. We flag a fund as delaying markdowns if the sum of its markdowns for the year immediately following fundraising is in the top tercile of all markdowns for the year after fundraising, measured in event time.

NAV Misstatement: GPs may boost IRRs by overstating or aggressively marking up the estimated values of illiquid portfolio investments around fundraising (i.e., NAV overstatement). Brown et al. (2019) find little to no evidence of NAV overstatement around fundraising among buyout and venture funds that successfully raise capital for a follow-on fund. However, GPs can also make their IRRs "pop" by *understating NAVs* if they subsequently exit the underlying investments at a higher market valuation than the one included in the IRR calculation. We flag a fund as understating NAVs around fundraising if its average NAV bias (the returns to NAVs not explained by cash flows or public market returns; discussed in Section 1) over the year before the fundraising quarter is in the bottom tercile of all NAV bias measurements for the year before fundraising, measured in event time.

Columns (2) and (3) of Table 2 present the results of these tests after removing funds flagged as consistent with particular manipulation strategies and re-estimating treatment effects. Column (2) reports results obtained after considering only one manipulation flag at a time. The strongest attenuations occur when funds flagged as engaging in quick flips (to −280 bps) or delaying markdowns (to −330 bps) are removed, indicating that these strategies explain roughly 40% and 30% of our headline result, respectively. The estimated effect of fundraising reduces to −420 bps after removing funds flagged as grandstanding and to −430 bps after removing funds flagged as understating NAVs.

Column (3) of Table 2 presents the results of these tests removing funds flagged as consistent with each manipulation strategy *cumulatively* and re-estimating treatment effects. Removing funds with more than one flag steps the headline result from −470 bps to a positive and insignificant point estimate of 140 bps, indicating that several flags are non-overlapping. These results suggest that conservatively calculating NAVs is an effective strategy for boosting IRRs when combined with quick flips. Figure 4 provides a visual summary of these results.

In our internet appendix, we conduct an additional series of tests examining how GPs boost IRRs that complement the decomposition presented in Table 2. We find that our estimated treatment effect concentrates among funds in the middle tercile of abnormal NAV returns (Tables IA14 and IA15). Additional results indicate that; fundraising events do not correspond to a change in NAV reporting (Table IA16), a \$1 distribution is associated with only about a \$0.90 decrease in NAVs (Table IA17 and Figure IA5, in the spirit of Kieser (2020)), worse-performing funds attempt to increase IRRs by exaggerating NAVs (Table IA18, mirroring Brown et al. (2019)), and NAV volatility is minimized during fundraising events (Table IA19 and Figure IA6).

The results in this subsection help mitigate the scope of a time-varying omitted factor: GPs exhibiting behavior consistent with IRR boosting techniques must also load on this omitted factor. Our IRR boosting results are also unlikely due to "luck." Under our fixed effects specifications, attributing our results to GPs getting lucky assumes that over funds' lives, GPs are, on average, most lucky with IRR outcomes during fundraising. In addition, as we will show, "luck" requires relatively implausible correlations in manager types; the propensity for GPs to receive lucky draws in performance outcomes during fundraising (but less so after) would also need to be positively correlated with the incentives for GPs to cater to LPs with boosted IRRs and smoothed NAVs.

2.1.3 Boost Duration

The results presented in Table IA20 indicate that IRR boosts are long-lived and persistent. Reported IRRs have an AR(1) coefficient of about 0.80 (between 0.78 and 0.96 depending on the specification), indicating that actions taken by GPs to boost IRRs remain in reported IRRs for several years, stretching beyond fundraising events (e.g., $0.96^{10\text{ years}\times 4\text{ quarters}} = 19.54\%$ remaining). Table IA21 provides evidence that GPs that boost the IRRs of fund #N while raising capital for fund #N+1 also tend to raise capital for additional funds beyond fund #N+1.

In total, our results indicate that GPs boost IRRs and do so primarily by adjusting the timing of cash flows. GPs that boost IRRs raise subsequent funds. Additionally, boosts in IRRs reported to LPs appear to be long-lived and persistent. Our findings are consistent with several boosting techniques proposed by Phalippou (2008), Lopez-de-Silanes et al. (2015), Barber and

Yasuda (2017), and Chakraborty and Ewens (2018) and also with recent work examining fund NAV exaggeration among buyout and venture GPs (Brown et al. 2019; Hüther 2021).

3 Catering Incentives

In this section, we relate catering incentives for fund GPs to estimates of IRR boosts and NAV smoothing. Our primary measure of catering incentives is the average weight of the fund in its' LPs' portfolios. We refer to this measure as "investor performance sensitivity." Formally:

$$\text{Investor Performance Sensitivity}_i = \frac{1}{J}\sum_{j \leq J} \frac{c_{ij}}{\text{AUM}_j}, \tag{2}$$

where i indexes the fund and c_{ij} denotes the value of LP j's commitment to fund i, which we scale by LP j's Assets Under Management (AUM) retrieved from Preqin in February 2022. We argue that GPs have relatively higher catering incentives if their funds occupy more of their LPs' portfolios. Our measure has the following intuition: GPs choose whether and how to boost IRRs or smooth NAVs based on benefits—including whether doing so is more valuable to its LPs. But GPs also consider costs—including whether doing so will hurt future performance or harm their chances of raising capital for a follow-on fund (if punished by their LPs). If a fund occupies more of its investors' portfolios, the returns its GPs report– and any boosting or smoothing that comes with the report– have a higher impact for fund LPs. If boosted IRRs or smoothed NAVs cater to LPs, then doing so is more likely to be a positive NPV project for the GPs with more "performance sensitive" LPs. In contrast, if the LPs' returns are less sensitive to the fund's reported returns, the benefits of boosting IRRs or smoothing NAVs are not as high. Lower benefits presumably make it less likely that manipulating IRRs or NAVs is a positive NPV project for the GPs.

For example, suppose the GPs of Fund ABC raised \$10 in capital consisting of; \$3 from CalPERS with AUM of \$100 (one of the most frequent public pension PERE investors), \$5 from TIAA with AUM of \$100 (one of the most frequent private sector pension PERE investors), and \$2 from the University of Michigan Endowment with AUM of \$50 (one of the most frequent endowment PERE investors). The GPs of Fund ABC have an investor performance sensitivity of 4% $\left(= \frac{1}{3} \times \left(\frac{\$3}{\$100} + \frac{\$5}{\$100} + \frac{\$2}{\$50}\right)\right)$, which is roughly the 75$^{\text{th}}$ percentile among funds in our sample.

The returns that the Fund ABC GPs report – and any boosting and smoothing embedded in these reports – are roughly 8× more impactful for the returns of its investors (CalPERS, TIAA, and the University of Michigan Endowment) than if the GPs of the fund managed only 0.5% of their LPs' assets (roughly the 25th percentile in our sample).

3.1 IRR Boosting and Catering Incentives

Our test relating catering incentives to IRR boosting is summarized as follows: fundraising events create an incentive to boost IRRs, but this boosting incentive is either amplified or attenuated by the strength of catering incentives the GP faces. Because fund fixed effects absorb the heterogeneity of investor performance sensitivities in our main specification, we assign funds to "high" and "low" investor performance sensitivity groups based on whether equation (2) for a given fund is above or below the median investor performance sensitivity for all funds (1.33%). We keep all unsuccessful fundraisers (never-treated funds) in each sub-sample. We then recalculate the effect of fundraising on reported IRRs following Section 2 within each sub-sample.

We present our results in Table 3. Columns (1) and (2) show that IRR boosts, estimated based on variation in the timing of fundraising events, average 640 bps among "high" investor performance sensitivity funds. In contrast, we estimate that IRR boosts average an insignificant 110 bps among "low" investor performance sensitivity funds. Although a LP's allocation to a single fund usually cannot comprise a large portion of the LP's assets, we estimate that these IRR boosts nonetheless increase the portfolio-level returns for some LPs. A back-of-the-envelope calculation indicates that the IRR boosts from a single fund add about 24 basis points of annualized returns for the median LP in high-performance sensitivity funds (≈ 640 bps boost × 3.72% median weight). In contrast, annualized returns increase by less than a basis point of annualized returns for the median LP in low-performance sensitivity funds (≈ 110 bps boost × 0.42% median weight).

In the remaining columns of Table 3, we repeat the analysis with permutations of equation (2). Specifically, we recalculate investor performance sensitivities, using only LP AUM allocated to (i) alternative assets, (ii) real estate assets, and (iii) private real estate assets. We retreive these data from 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 but have 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 IRRs within each sub-sample of high and low investor performance sensitivities. Panel A displays results for investor performance sensitivity calculated using LPs' total AUM. 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 monotonic declines in reported IRRs after fundraising (relative to imputed counterfactuals), whereas the below-median groups show moderate or no declines in IRRs after fundraising.

We also examine GP catering incentives using different subsets of fund LPs in our internet appendix. We find similar cross-sectional variation in IRR boosting if we calculate fund-level investor performance sensitivity using only commitments from anchor LPs or using only commitments from non-anchor LPs, where anchor LPs are identified based on commitment amounts, LP AUM (and capacity to commit to future funds), or LP investing histories with the fund GPs (Table IA22). Similar cross-sectional variation in IRR boosting also attains if we calculate fund-level investor performance sensitivity using only commitments from U.S. public pension LPs or using only commitments excluding U.S. public pension fund LPs (Tables IA23 and IA24).

The results presented in Table IA25 indicate that the findings presented in Table 3 are similar if we; do not impute LP commitments, use historical LP AUM, or permute our measure using value-weighting or median aggregations. Similar results also attain if we scale LP commitments by LPs' previous PE fund commitments rather than LPs' AUM (Table IA26) or use more granular splits of investor performance sensitivity (Table IA27). Additionally, Table IA28 and Table IA29 respectively display similar results for IRR boost decompositions and AR(1) coefficients after conditioning on investor performance sensitivity.

We interpret the results in this section as consistent with our catering hypothesis. Our findings indicate that investor performance sensitivity is an important determinant of IRR boosts. In the context of our stylized framework, the evidence points to catering incentives as amplifying the benefits of reporting persistently boosted headline IRRs to LPs for PERE fund managers.

3.2 Return Smoothing and Catering Incentives

In this section, we relate our measure of GP catering incentives to return "smoothness" – the extent to which fund NAV returns fail to immediately reflect changes in contemporaneous market variables. Figure 6 plots the time series of returns for a REIT index (the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs), and a PERE index downloaded from Preqin (the Real Estate Opportunistic Private Capital Quarterly Index). The annualized standard deviation of returns on the REIT index is 20.9%, while the annualized standard deviation of returns on the PERE index is 11.4%. Regressing returns of the Preqin PERE index on 0-, 1-, 2-, and 3-quarter lags of the REIT index simultaneously results in coefficients of 0.17, 0.11, 0.12, and 0.14, respectively, each of which is significant at the 1% level. Additionally, the REIT index has an AR(2) of (.14, −.21) and the Preqin PERE index has an AR(2) of (.33, .44). Taken together, these results are consistent with aggregate smoothing in PERE returns.

We examine whether GP catering incentives are related to NAV smoothing by estimating regressions of the form:

$$r_{it}^{\text{NAV}} = \sum_{k=0}^{k=N} \lambda_k r_{t-k}^b + \beta_j (\text{IPS}_i \times r_{t-k}^b) + \gamma \text{IPS}_i + \delta X' + \psi_i + e_{it}, \tag{3}$$

where i indexes the fund, t indexes the year-quarter of the observation, r_{it}^{NAV} equals the quarterly NAV return of a fund accounting for quarterly cash flows, IPS_i is shorthand for investor performance sensitivity, r_{t-k}^b denotes quarterly benchmark returns lagged by k quarter(s), X' denotes a vector of controls (including quarterly cash flows, fund size, and an indicator for whether the GPs of the fund ultimately raised capital for a follow-on fund), and ψ_i denotes a vintage year fixed effect (ensuring the funds are exposed to similar economic conditions). In our main specifications, we choose $0 \leq k \leq 3$, capturing the past year (four quarters) of public market returns; however, our results are robust to including almost two years of lagged benchmark returns (Figure IA7). We use the FTSE REIT index as the public market benchmark but similar results attain using value-weighted S&P 500 returns instead (Table IA30).

The coefficients of interest are the marginal pass-throughs of each benchmark return to

NAV returns. For benchmark return r^b_{t-k}, the pass-through estimate equals $\lambda_k + \beta_k(\text{IPS}_i)$; the direct relationship between benchmark returns and NAV returns plus any amplification or attenuation due to differences in how benchmark returns are incorporated into asset values by GPs of funds facing different catering incentives. The null hypotheses are that $\lambda_k = 0$ if $k > 0$ – indicating that changes in NAVs only reflect contemporaneous changes in market prices – and that $\beta_k = 0$ – indicating that catering incentives do not alter this relationship.

We present the results of these regressions for up to three lags of benchmark returns in Table 4. In all specifications, the coefficients on the REIT benchmark returns (λ_k) are positive and statistically significant. These results indicate that the quarterly NAV returns for PERE funds in our sample reflect both contemporaneous and lagged returns on the REIT benchmark. Focusing on the results presented in column (4) – where we include contemporaneous benchmark returns alongside three quarterly lags – the results show that funds that comprise a larger fraction of their investor's portfolios (on average) report NAV returns that are less reflective of contemporaneous benchmark returns but more reflective of benchmark returns from three quarters earlier.

To visualize these results, Figure 7 plots the percentage change in market return loadings due to GP catering incentives (investor performance sensitivity) based on the results presented in column (4) of Table 4. Specifically, we plot the quantity Investor Performance Sensitivity$_i$ $\times$ β_k/λ_k after varying the level of investor performance sensitivity to be 0.42%, 1.33%, or 3.72%– the 25$^{\text{th}}$, 50$^{\text{th}}$, and 75$^{\text{th}}$ percentiles of investor performance sensitivity, respectively– for each lagged benchmark return ($k \in \{0, 1, 2, 3\}$). Funds at the 75$^{\text{th}}$ percentile of investor performance sensitivity report NAV returns that load about 7% more on three quarter lags of public market returns and about 3% less on contemporaneous public market returns, relative to an unconditional result (with an investor performance sensitivity of 0). In contrast, funds at the 25$^{\text{th}}$ percentile of investor performance sensitivity report NAV returns that only load about 1% more on three quarter lags of public market returns and about 0.4% less on contemporaneous public market returns, relative to an unconditional result (with an investor performance sensitivity of 0).

We also examine how smoothing relates to LP commitments to PERE funds in our internet appendix. In the time series, we document that a higher pass-through of benchmark returns to NAV returns (less insulation) is negatively associated with aggregate PERE fund commitments the following year (Figure IA8). Additionally, in our fund-quarter panel, we find that interim NAV return volatility is minimized during fundraising events (Figure IA6 and Table IA19).

The results in this section indicate that the GPs of funds that face higher catering incentives report smoother valuations—reporting NAVs that take longer to reflect market pricing. The evidence points to catering incentives as amplifying the benefits of smoothing NAV returns for PERE fund managers. These findings complement Stafford (2022) and Brown et al. (2023), who provide evidence that PE GPs report smooth returns and valuations, on average.

3.3 LP Agency Frictions and GP Catering Incentives

In this section, we examine the source of a GP's catering incentives. We posit that boosted IRRs and smoothed NAVs are more likely to cater to LP investment managers if the LP investment managers face stronger agency frictions within their LP organizations. We test this hypothesis in our sample of U.S. defined benefit public pension fund LPs. The data are available and previous literature highlights agency conflicts in their investment structures.

We examine agency frictions in public pension plans along several dimensions. Our main set of tests considers the relationship between PERE fund commitments and political representation on pension boards. Andonov et al. (2018) find that PE investment decisions made by politically appointed trustees are related to political expediency and political contributions from the finance industry, resulting in underperformance on PERE investments in a way that appears unrelated to the financial expertise of the trustees. To complement these tests, we also examine the relationship between LP commitments, pension size, reported pension funding ratios, and CIO pay, as these variables may also proxy for agency frictions between plan CIOs, boards of trustees, and pension beneficiaries. Andonov et al. (2017) show that lower funding ratios can induce boards to "risk up" their portfolios to improve their reported funding ratios. Dyck et al. (2021) argue that an agency-based mechanism is at play: pension managers prefer to increase their *reported* funding ratios through risky asset exposure rather than disclose funding shortfalls to legislatures. Dyck et al. (2021) also propose that pension boards face "outrage risk": the reluctance of many trustees to compensate their CIOs at market rates because doing so might upset their plan beneficiaries, meaning that agency costs from outrage risk are relatively higher among pension plans that pay their investment managers relatively less.

We present our results in Table 5. We regress the public pension LP's commitment to a given PERE fund, scaled by the pension fund's assets (as of the commitment year) on the composition of the board of trustees, the reported funding ratio of the pension plan, the compensation of the CIO, the size of the pension fund in the previous year, and previous commitments (as a percentage of plan assets) made by the pension. Regression samples exclude the top 1% and the bottom 1% of LP Commitments/LP Assets. Our results are robust to adjusting this restriction. Most specifications include fixed effects for the state of the pension and the year of the commitment, allowing for differential baseline allocation outcomes across states and over time. Accordingly, our tests compare a given commitment to all other commitments made by pensions in the same state (e.g., California) in the same year (e.g., 2005). We additionally include controls for the investment performance and PERE investing history of the pension fund alongside controls for the realized performance and size of the PERE fund, further limiting the role of differential allocation strategies and investment outcomes across LPs. We cluster standard errors at the pension fund level.

The results displayed in Table 5 indicate that pensions with boards characterized by a higher percentage of state-appointed and state-ex officio trustees tend to make larger commitments (as a percent of pension assets) to a given PERE fund, increasing the catering incentives of their GPs. A 28 percentage point (one standard-deviation) increase in the proportion of the board consisting of state-political trustees is associated with approximately an incremental 9 bps of pension assets allocated to a given fund ($\approx 28\% \times 33.4\%$ regression coefficient $/100$), relative to the omitted category of participant-appointed board members. This result represents an economically significant increase, given that the average commitment to a PERE fund equals 0.33% of the public pension fund's assets ($70 million).

We also find that previous LP commitments (as a percentage of plan assets) are positively associated with future commitments as a percentage of pension plan assets, and that managers of smaller and worse funded pension funds tend to allocate a larger percentage of plan assets to a given PERE fund. Additionally, pensions that compensate their CIOs less tend to make larger commitments (as a percentage of their assets) to a given PERE fund, but not after controlling for the size of the pension plan. We also calculate each fund's investor performance sensitivity excluding the commitment made by the LP of interest (the dependent variable) and find that this "leave-one-out" fund level investor performance sensitivity measure is positively associated with individual LP commitments as a percentage of pension plan assets; however, this relationship is not statistically significant.

Columns (6) and (7) indicate that boards characterized by a higher percentage of state-appointed and state-ex officio trustees tend to allocate a larger fraction of their assets to a given PERE fund after including other pension characteristics of interest. The reported funding ratio coefficient retains its sign but remains statistically significant only in the sub-sample of commitments where CIO compensation data are available. In column (8), we repeat our tests after including a PERE fund fixed effect, meaning that we are comparing a given allocation to all other commitments made by other pensions located in the same state to the same fund (implicitly with the same vintage). The coefficients presented in column (8) are of the same sign and similar in magnitude to coefficients in other columns, indicating that features specific to the fund are unlikely to explain our results. Overall, the results presented in Table 5 indicate that public pensions exhibiting higher degrees of agency frictions are related to the propensity for public pension investment managers to make allocations that increase the catering incentives of GPs.

We discuss two additional points. First, although public pensions with relatively higher agency frictions may attract relatively lower-skilled investment managers and trustees, it is unlikely that investment skill differentials across pensions are sufficiently large to drive our results. Our tests include PERE fund performance controls which partials out the positive relationship between LP fund weights and PERE performance arising if higher-skilled investment managers tend to overweight better-performing funds and lower-skilled managers tend to overweight worse-performing funds. Second, although GPs raise capital from other LPs – such as endowments and private sector pensions – additional results confirm that public pension LP allocation weights predict GP propensities to boost IRRs. GP catering incentives calculated using only public pension data (ignoring all other LP classes) continue to predict GP tendencies to boost IRRs (Table IA23).

Our results indicate that a GP's incentives to report boosted IRRs and smoothed NAVs that cater to their LPs are driven, in part, by the agency of investment managers and board trustees responsible for the investments of its public pension LPs. Public pension investment managers flagged as facing higher agency frictions are more likely to increase the catering incentives of their GPs by allocating a larger fraction of their assets to the fund– making the PERE fund's reported returns and volatility relatively more impactful for their pension fund's returns.

3.4 Pension Board Composition Changes

To further examine the relationship between GP return manipulation and LP agency frictions, we construct a complementary agency-based measure of a GP's catering incentives not reliant on cross-sectional variation in investor performance sensitivity or fundraising events: the average fraction of a fund's public pension LP board trustees that are politically appointed in a given year. Formally:

$$\text{Avg. \% State-political}_{it} = \frac{\sum_j c_{ij} \times \text{\% State-political}_{jt}}{\sum_j c_{ij}}, \tag{4}$$

where i indexes the PERE fund, t indexes the year of the observation, j denotes public pension LP j of fund i, c_{ij} indicates the dollar value of the capital commitment LP j made to fund i, and % State-political$_{jt}$ calculates the fraction of public pension j's board of trustees that are politically appointed in year t (weighted by the dollar value of LP commitments, c_{ij}). Pension board compositions are relatively stable over time and within PERE fund lives; however, if GP catering incentives relate to agency frictions within LPs, we would expect increases in LP board politicization (which reflect increases in the strength of agency frictions faced by public pension LP j) to increase the catering incentives for GP i. Conversely, public pension LP board de-politicization can decrease GP catering incentives.

Table IA32 lists our sample of 44 public pension board composition changes. Table IA33 indicates that these pension board composition changes are uncorrelated with the performance of the pension fund (measured over 1-, 5-, and 10-year horizons), the performance of other pensions in the same state, or the performance of PERE funds in our sample that the pension invested in. Pensions with worse reported funding ratios are more likely to change their board composition; however, lower reported funding ratios are correlated with both increases *and* decreases in trustee political representation.

We present our first set of results in Table 6, regressing PERE funds' annual performance on the political composition of the PERE funds' public pension LP board trustees in the same year (equation (4)). The unit of observation is the PERE fund-year (rather than the PERE fund-quarter) because board trustee data are available at an annual unit of observation. The results presented in columns (1) – (3) measure fund performance using annual NAV returns, and the results presented in columns (4) – (6) measure fund performance using annual NAV bias (excess NAV returns). We use NAV returns, rather than IRRs, to better capture the timing of any GP response.

All regression specifications include fund and year fixed effects, allowing for differential outcomes across funds and over time. Regressions presented in columns (2) and (5) add controls including: annual PERE fund calls and distributions scaled by fund size, Brown et al. (2019) fund-timing and peer-chasing (measuring incentives for GPs to exaggerate NAVs during the middle of fund lives), and the commitment-weighted average pension LP reported funding ratio in the PERE fund-year cell. The regressions presented in columns (3) and (6) reflect our most stringent specifications, adding fund-age and post-fundraising fixed effects to allow for differential outcomes across fund ages and fundraising statuses. We cluster standard errors at the fund level.

Across all specifications, the results displayed in Table 6 indicate that annual NAV returns and excess NAV returns positively covary with the fraction of a fund GP's public pension LP board trustees that are politically appointed in a given year. In addition, placebo tests in our internet appendix indicate that the composition of other public pension trustees does not covary with PERE fund NAV return levels (Table IA34).

Table 7 presents our second set of results. We estimate regressions of the form:

$$
\begin{aligned}
r_{it}^{\text{NAV}} = \sum_{k=0}^{k=1} \lambda_k r_{t-k}^{b} + \beta_k((\text{Avg. \% State-political})_{it} \times r_{t-k}^{b}) \\
+ \gamma(\text{Avg. \% State-political})_{it} + \delta X' + \Omega_i + e_{it},
\end{aligned}
\tag{5}
$$

where i indexes the fund, t indexes the year of the observation, r_{it}^{NAV} equals the annual NAV return of a PERE fund accounting for annual cash flows, r_{t-k}^{b} denotes annual benchmark returns lagged by k year(s), X' denotes a vector of controls (the same set of controls used for regressions presented in Table 6), and Ω_i denotes a PERE fund fixed effect. Columns (1) and (2) present results using the FTSE REIT index as the public market benchmark, and columns (3) and (4) present results using value-weighted S&P 500 returns instead. We cluster standard errors at the year level.

Similar to the smoothing tests presented in Table 4, the coefficients of interest are the marginal pass-throughs of each benchmark return to NAV returns. The results presented in Table 7 show that the coefficients on the REIT returns (λ_k) are positive and statistically significant, but only for one-year lags of returns. S&P 500 return coefficients are not statistically significant.

These results indicate that annual NAV returns for PERE funds in our sample reflect both contemporaneous and lagged returns on public market benchmarks, but with a weaker pass-through compared to quarterly pass-throughs. Focusing on the interaction coefficients (β_k), the results indicate that PERE funds with more politically appointed public pension trustees (on average) report NAV returns that are less reflective of contemporaneous benchmark returns but more reflective of benchmark returns from the previous year. Placebo tests in our internet appendix indicate that the composition of other public pension trustees does not covary with PERE fund NAV return smoothness (Table IA35).

The results in this section further support our agency-driven catering hypothesis. Public pension agency constraints, as measured by the fraction of board trustees that are politically appointed within a given year, positively covary with both PERE fund NAV return levels and smoothness. These findings are consistent with LP agency-driven catering incentives amplifying the benefits of boosting and smoothing NAV returns for GPs.

3.5 Additional Economic Frameworks

Our previous results are consistent with a mechanism where GPs boost and smooth returns to cater to agency-driven LP demand for manipulated returns. To examine the scope of alternative mechanisms, we relate these results to other potentially relevant economic frameworks for analyzing the observed cross-sectional variation in IRR boosting and NAV smoothing. Specifically, we examine frameworks related to deception, GP reputation, fund risk, and LP monitoring incentives.

3.5.1 Deception

One possible economic framework is that in the cross-section of PERE funds, PERE GPs with higher catering incentives are more likely to boost returns and mask risk in a way that deceives LP allocators rather than in a way that more directly responds to agency frictions in their LPs' organizations. This deception framework implies that investor performance sensitivity would have to be positively correlated with LPs' likelihood of being deceived by manipulated interim returns. The first way we examine this possibility is by relating measures of LP sophistication to boosting, smoothing, and investor performance sensitivities. Lerner, Schoar, and Wongsunwai (2007) and Cavagnaro, Sensoy, Wang, and Weisbach (2019), for example, provide evidence of heterogeneity in LP sophistication at PE investing. If GPs manipulate returns in attempts to mislead their investors, we would expect smoothing and boosting to occur more among funds with less sophisticated or experienced LPs than among funds with more sophisticated or experienced LPs.

We first characterize fund LPs by the average realized performance of the LP's investments made before the time of commitment (measured using TVPI). We measure LP performance using only PERE investments because LPs often have separate investing experiences for each asset class. In addition, we measure LP familiarity with a GP using the cumulative number of commitments the LP made to a given GP before making the current commitment. We also measure LP familiarity with PERE as the number of previous PERE investments the LP has made to any PERE GP. We scale this number by the average number of cumulative PERE investments per LP at the time of commitment to better capture the relative experience of the LP and avoid under-weighting earlier commitments. We average each measure at the fund level and assign funds to "high" and "low" groups for each measure based on whether it is above or below the sample median. Table IA36 provides evidence that GPs tend to boost IRRs if their LPs have generally invested in better-performing PERE funds or if their LPs have made more investments in their previous funds.

Table 8 presents results considering whether catering incentives and the three measures of LP sophistication jointly explain variation in IRR boosts. For this analysis, we double sort funds by "high and "low" investor performance sensitivity groups and also on whether the LP characteristics are classified as "high" or "low," creating a 2×2 grid of classifications.[11] We then recalculate the effect of fundraising on reported IRRs within each sub-sample, always retaining unsuccessful fundraisers. The results displayed in columns (1) and (2) show that estimated IRR boosts are economically and statistically significant for all sub-samples of funds with "high" performance sensitivity investors, regardless of variation in investor characteristics. However, estimates of IRR overstatement are not significant among the funds with "low" performance-sensitivity investors– also regardless of investor characteristics. The remaining columns indicate that these results are robust to permutations of our measure of GP catering incentives.

[11] High versus low classifications are always assigned using the full sample of funds, so for example, whether a fund is classified as having better-performing LPs is *not* conditioned on whether the GP faces high or low catering incentives. Accordingly, variation in the number of observations in regression samples partially reflects correlations between incidences of each classification.

These results are inconsistent with the deception framework. This alternative deception mechanism would require that LP deception be positively correlated with past LP performance and PERE experience, which is difficult to reconcile with traditional notions of sophistication. Moreover, how some LP allocators discuss their PE commitments, which acknowledges that returns are smoothed (e.g., Maynard (2015)), is inconsistent with allocators being deceived.

3.5.2 GP Reputation, Fund Risk, and LP Monitoring

We also consider additional fund characteristics that may alter the costs and benefits of manipulation for GPs. GPs might face differential costs and benefits from manipulating returns conditional on their reputation (Barber and Yasuda 2017). GPs market PERE funds that pursue riskier investment strategies using higher target IRRs (e.g., Riddiough (2022)), which may also affect the NPV of manipulating returns. LPs might also be less likely to monitor GPs if LP ownership is not concentrated, which hampers collective action, in the spirit of Shleifer and Vishny (1986).

We proxy for fund reputation based on the fundraising history of its GP. We classify funds as belonging to a "high-reputation" GP if the GP raised at least three funds with cumulative commitments exceeding \$1.5 billion before starting the fund. Otherwise, the fund belongs to a "low-reputation" GP, similar to the definition employed by Barber and Yasuda (2017). We proxy for fund risk using funds' stated investment strategies. We classify a fund as "high-risk" if it pursues an opportunistic or distressed investment strategy and "low-risk" otherwise (core, core-plus, or value-added). Lastly, we proxy for LP ownership concentration using the Herfindahl–Hirschman index (HHI) of a fund's capital commitments. A fund has a "high" concentration of investors if the fund's HHI is above the sample median and a "low" concentration (dispersed) investor base otherwise. Table IA36 provides evidence that GPs tend to boost IRRs if they have "dispersed" investors or they manage high-risk funds. There is also evidence of boosted IRRs among low and high-reputation managers.

Table 9 presents results considering whether catering incentives and the three sets of fund characteristics jointly explain variation in IRR boosting. In parallel to the analysis presented in Table 8, we double-sort funds based on high/low-performance sensitivity and fund characteristics. The results presented in column (1) show that the estimated effects of fundraising on reported IRRs are negative and statistically significant among funds with "high" performance sensitivity investors, regardless of variation in fund characteristics. In contrast, the results presented in column (2) show no evidence of statistically significant IRR boosting among funds with "low" performance sensitivity investors– also regardless of variation in fund characteristics. The remaining columns confirm these results are robust to alternative measures of GP catering incentives.

Table IA37 presents complementary results considering additional characteristics that attain similar conclusions. Table IA38 displays results indicating that the relationship between NAV returns, benchmark returns, and catering incentives presented in Table 4 – where funds with higher investor performance sensitivity report smoother NAV returns – is robust to including additional fixed effects or controls for measures of LP sophistication and these supplementary characteristics.

Overall, we interpret our results as most consistent with a mechanism where GPs boost and smooth returns to cater to agency-driven LP demand for manipulated returns. An alternative mechanism requires, for example, unobserved variation to be (i) positively correlated with investor performance sensitivity and variation in LP board politicization and (ii) uncorrelated with several measures of fund characteristics and investor sophistication.

4 Conclusion

The central conclusion of our paper is that some PERE GPs report boosted and smoothed returns to cater to their LPs. Doing so allows their LPs to report higher headline returns and artificially lower the volatility of their investments. This catering view of return manipulation is consistent with the LP preference to access commercial real estate investments through PERE funds rather than better-performing, marked-to-market REITs.

Using a difference-in-differences analysis exploiting staggered fundraising events and institutional features of PE fundraising to identify variation in GP boosting incentives, we find that cross-sectional variation in GP catering incentives predicts IRR boosting. Conditional on raising capital for a follow-on fund, GPs facing higher catering incentives report IRRs that are boosted by about 640 bps. However, we fail to find evidence that GPs raising capital for follow-on funds with relatively weaker catering incentives boost IRRs. Our results indicate that GPs boost IRRs primarily by shifting the timing of cash flows to LPs, and the LPs of high-performance sensitivity funds receive boosted IRRs strong enough to distort LP-level IRRs for up to several years.

GP catering incentives also predict the "smoothness" of fund NAV reports. On average, quarterly NAV returns reflect only about 13% of contemporaneous market returns – insulating LPs from market fluctuations. In the cross-section, GPs that face higher catering incentives report NAVs that take longer to incorporate market fluctuations than do GPs that face lower catering incentives. Additional time-series and panel tests are consistent with the idea that smoothed NAV returns and boosted IRRs attract LP capital commitments.

Our results align with a simple explanation for this catering phenomenon: some PE investors face agency frictions within their organizations that make manipulated interim returns attractive. LP investment managers often face shorter investment horizons than their principals (such as taxpayers and pension beneficiaries) and may benefit from boosted and smoothed PERE returns. Cross-sectional tests in our sample of U.S. defined benefit public pension funds support this hypothesis. We find that managers of pension plans characterized by several agency frictions, including higher political representation on plan boards (the composition of which is relatively constant over time), worse reported funding ratios, lower CIO compensation levels, and lower levels of plan assets, tend to make larger commitments (as a fraction of plan assets) to a given PERE fund, which, in doing so, increases the catering incentives of their GPs.

Overall, our results point to 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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Figure 1: Reported IRRs

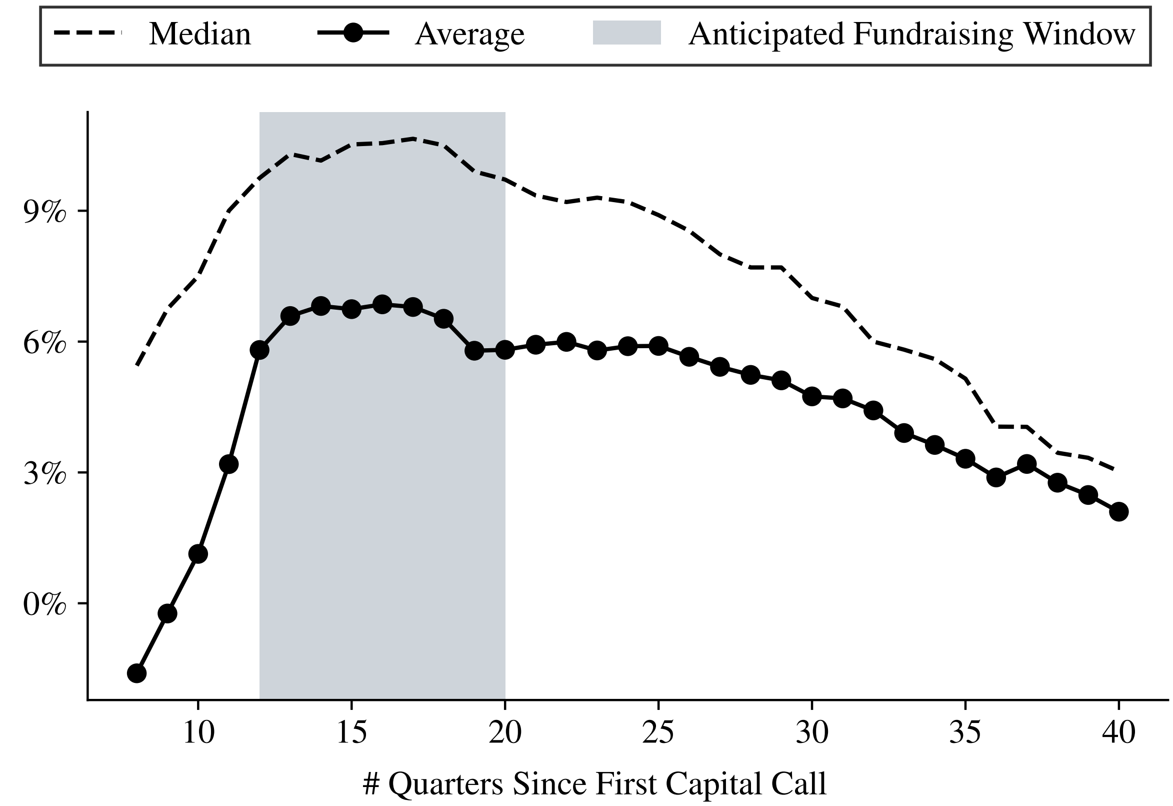

Figure 1: Plots the average and median IRRs since the first capital call for 416 out of 448 funds in our sample where the fund GPs raised capital for a follow-on fund. IRR data come from Cambridge Associates and include PERE funds with a vintage year between 2001 and 2014 that follow an opportunistic, value-added, distressed, core, or core-plus strategy. Reported IRRs are annualized, net-of-fees, and "to-date" measures, reflecting cumulative cash-flows over the funds' lives and fund net asset values as of a given quarter. The plot includes quarters 8 through 40 in the fund's life. The shaded box denotes years three through five, where PE participants typically expect a fundraising event to occur. The sample attenuates in later cells.

Figure 2: Reported IRRs Around Fundraising

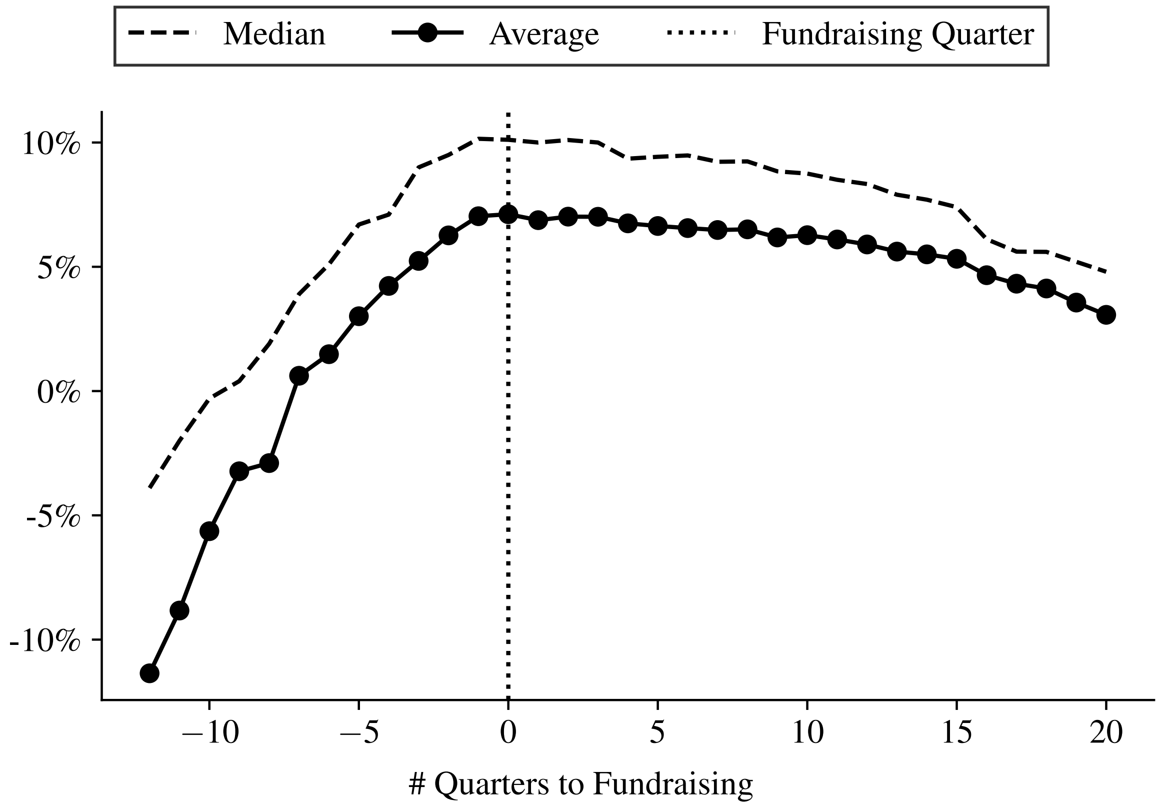

Figure 2: Plots the average and median IRRs relative to the fundraising quarter for 416 out of 448 funds in our sample where the fund GPs raised capital for a subsequent fund. Reported IRRs are annualized, net-of-fees, and "to-date" measures, reflecting cumulative cash-flows over the funds' lives and fund net asset values 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 GP at least three years after the current fund's vintage year. If the follow-on fund is identified but its capital call date is missing, the fundraising quarter is assumed to be the median time to raise capital for a follow-on fund for other funds with the same vintage year.

Figure 3: Fundraising and IRRs – Event Study Plot

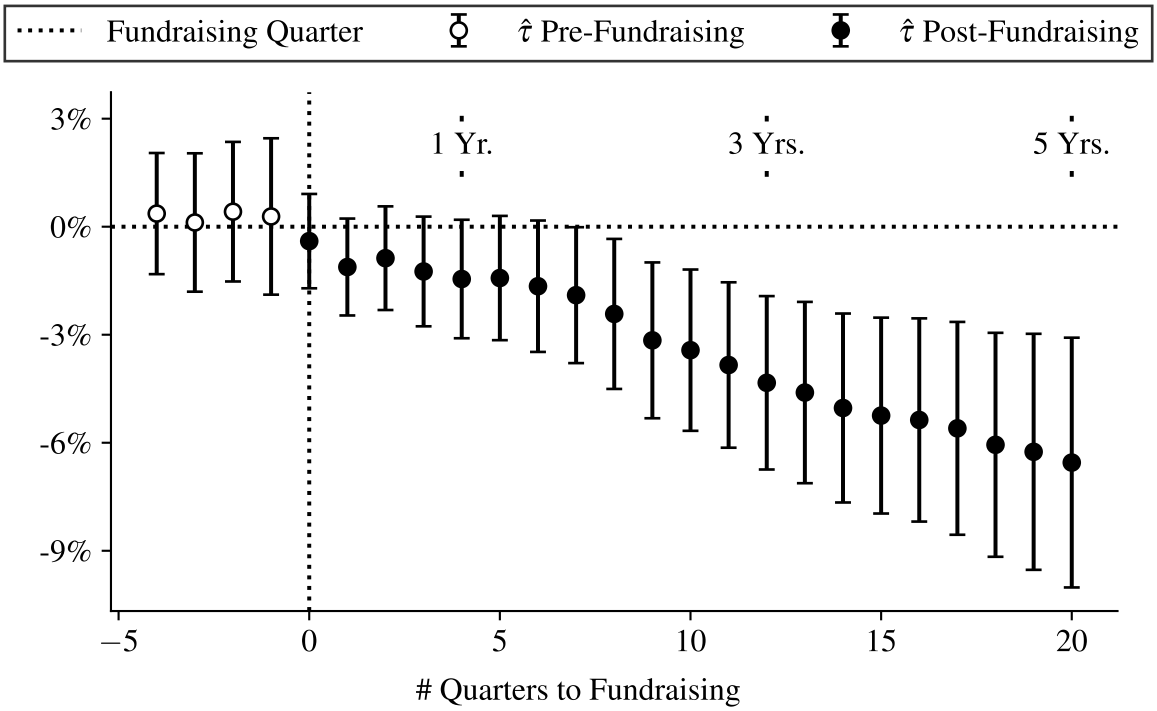

Figure 3: Plots dynamic difference-in-differences estimates of the effect of fundraising on reported IRRs using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. IRR reports for each fund are annualized, net-of-fees, and "to-date" measures, reflecting cumulative cash flows over the funds' lives and NAVs 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-fundraising coefficient estimates. Calculations use fund and year-quarter fixed effects, controls include one quarter lags of PME and NAV, and standard errors are clustered at the fund level.

Figure 4: IRR Boost Decomposition

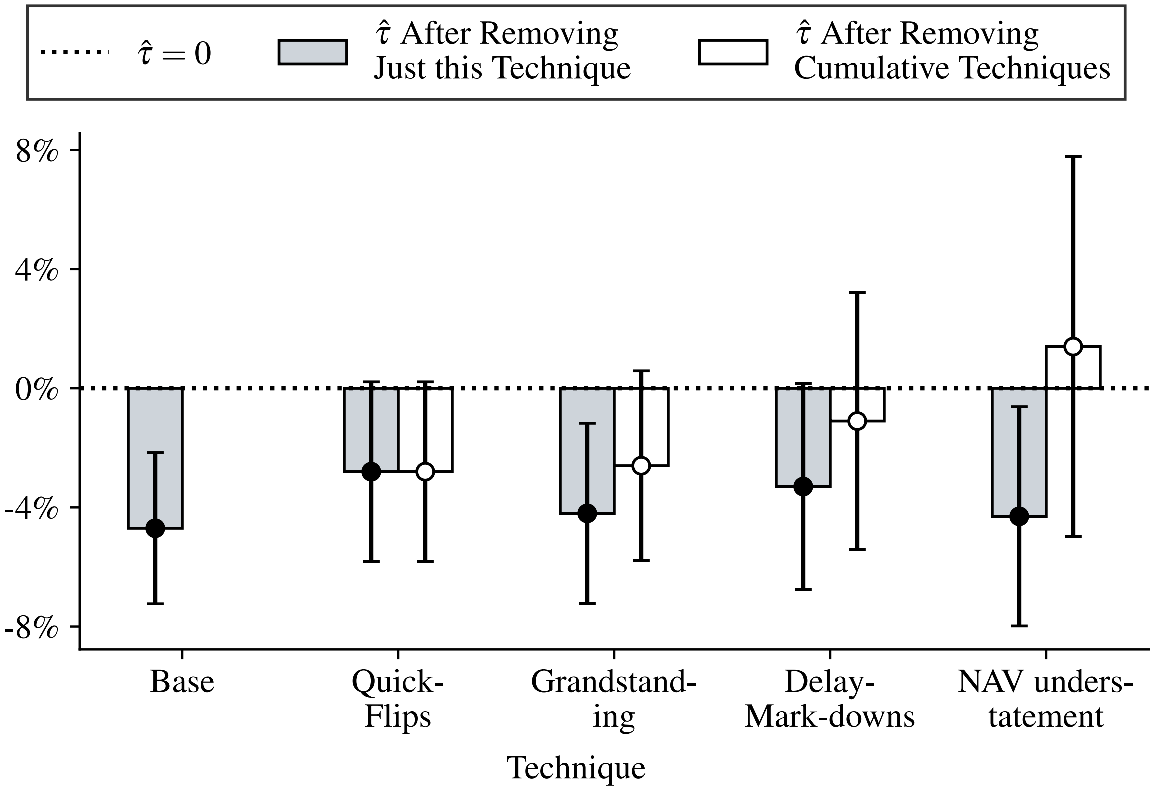

Figure 4: Plots difference-in-differences estimates of the effect of fundraising on reported IRRs, after removing funds that conform to particular IRR boosting techniques using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Section 2.1.2 describes each technique in detail. Filled circles denote the estimated treatment effect after accounting for an individual boosting strategy and unfilled circles denote the treatment effect after accounting for cumulatively removed boosting strategies. Vertical lines denote 95% confidence intervals. The resulting sub-samples keep all unsuccessful fundraisers. Calculations use fund and year-quarter fixed effects, controls include one quarter lags of PME and NAV, and standard errors are clustered at the fund level.

Figure 5: Catering Incentives and IRR Boosting– Event Study Plots

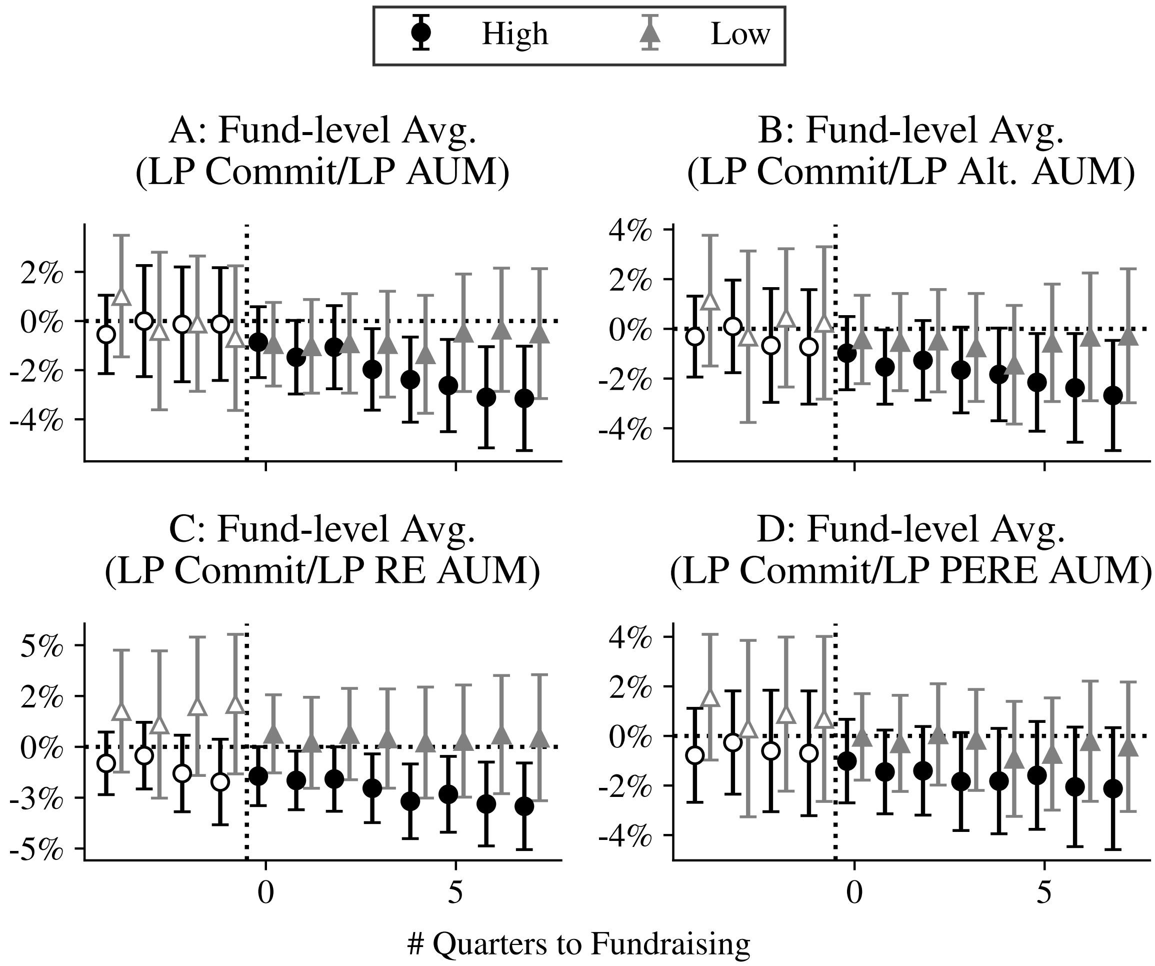

Figure 5: Plots dynamic difference-in-differences estimates of the effect of fundraising on reported IRRs, after partitioning the sample of funds on measures of investor performance sensitivity using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Panel titles indicate the investor performance sensitivity measure. Investor performance sensitivity is defined in equation (2) and equals the average weight of a fund in its LPs portfolios. "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 retain all unsuccessful fundraisers. 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-fundraising coefficient estimates. Calculations use fund and year-quarter fixed effects, controls include one quarter lags of PME and NAV, and standard errors are clustered at the fund level.

Figure 6: Time-Series of Index Returns

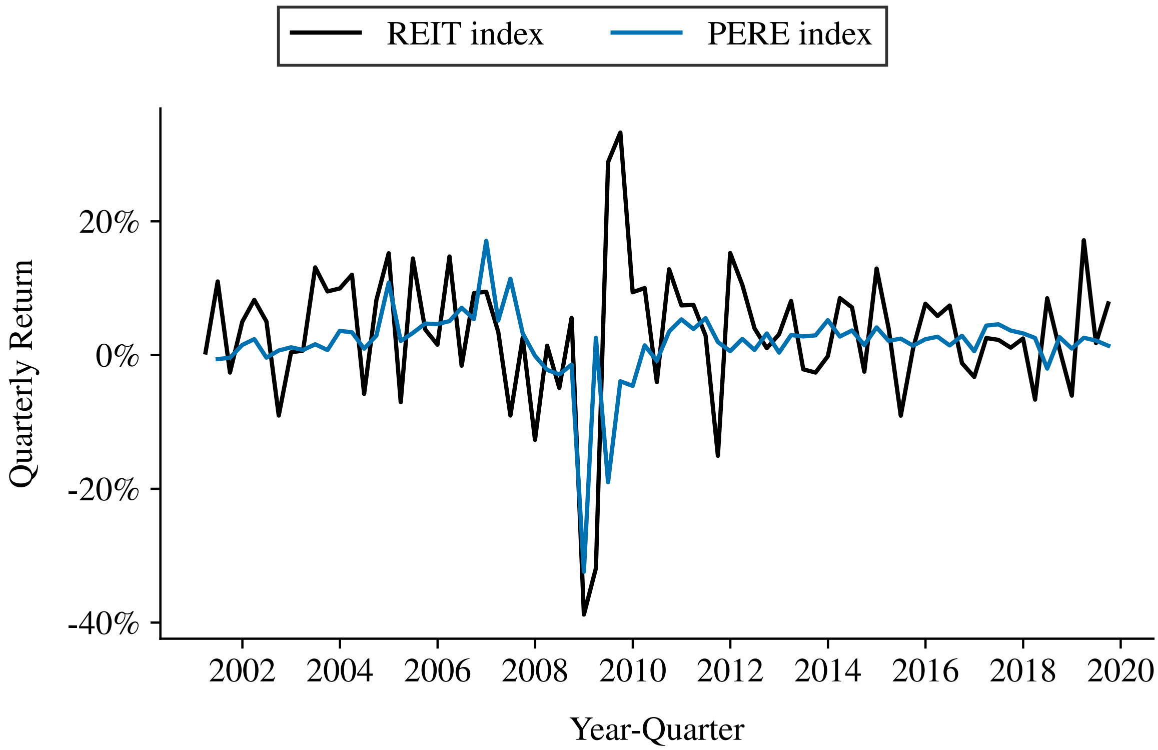

Figure 6: Plots quarterly returns for a REIT index (black) and a PERE index (blue). The REIT index is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. The blue PERE index is the Preqin Real Estate Opportunistic Private Capital Quarterly Index. The Preqin index is re-based to 2001.

Figure 7: Catering Incentives and Return Smoothing

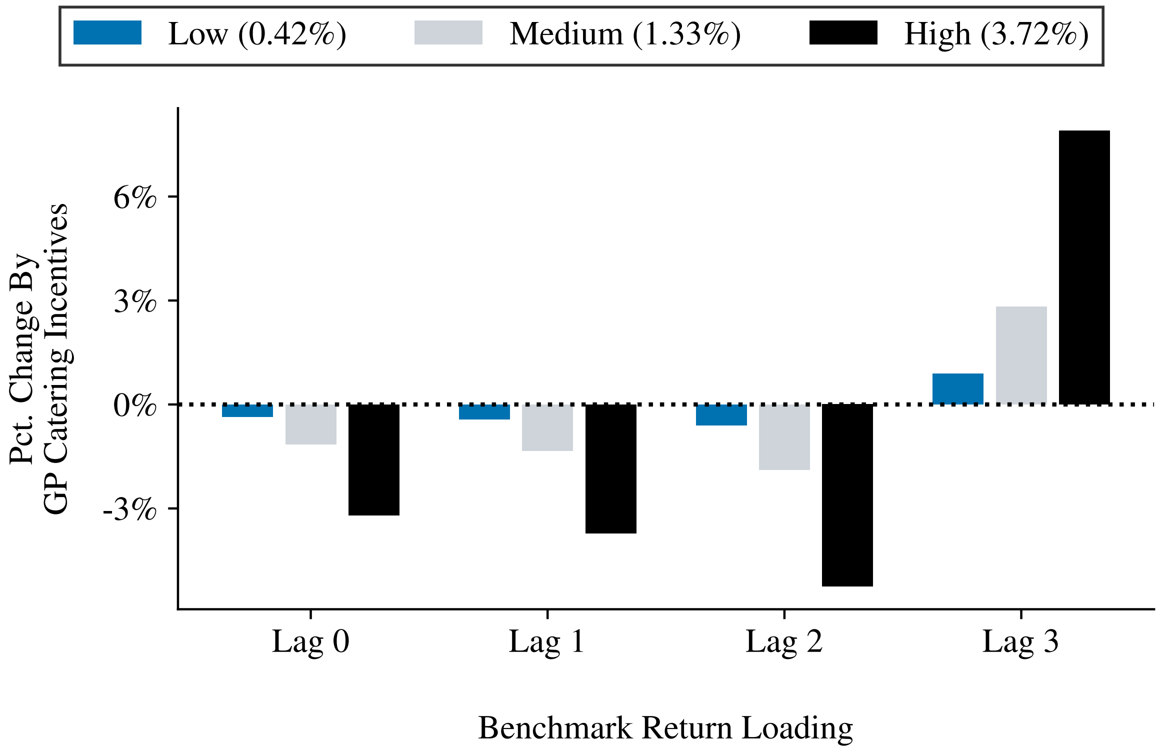

Figure 7: Plots the percentage change in contemporaneous and lagged benchmark return loadings after varying the level of investor performance sensitivity to be 0.42%, 1.33%, or 3.72%– the 25th, 50th, and 75th percentiles of investor performance sensitivity, respectively. Benchmark return loadings are obtained from the regression: $r_{it}^{NAV} = \sum_{k=0}^{k=3} \lambda_k r_{t-k}^{b} + \beta_k(\text{IPS}_i \times r_{t-k}^{b}) + \gamma \text{IPS}_i + \delta X' + \psi_i + e_{it}$, where i indexes the fund, t indexes the year quarter of the observation, r_{it}^{NAV} equals the quarterly NAV return of a fund accounting for quarterly cash flows, IPS_i is shorthand for investor performance sensitivity (our main measure of catering incentives; equation (2)), r_{t-k}^{b} denotes quarterly benchmark returns lagged by k quarter(s), X' denotes a vector of controls (including quarterly cash flows, fund size, and whether the GPs of the fund ultimately raised capital for a follow-on fund), and ψ_i denotes a vintage year fixed effect. The benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. Table 4 contains the results of this regression. Bars in the plot equal $\text{IPS}_i \times \beta_k/\lambda_k$, where k denotes the applicable lag, using the results from the regression of NAV returns on benchmark returns.

Table 1: 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
r_{it}^{NAV}	17,641	-0.00	0.19	-0.34	-0.01	0.00	0.05	0.23
NAV bias	17,648	-0.02	0.21	-0.40	-0.09	-0.01	0.05	0.29
				Panel B: Fund Level				
Vintage Year	448	2007.56	2.85	2003	2005	2007	2010	2012
Fund Size ($MM)	448	773.51	1,198.96	73.98	236.38	460.00	800.00	2,484.35
# of Previous Funds	448	4.87	6.94	0.00	1.00	2.50	6.00	16.65
Final IRR	448	0.05	0.15	-0.14	-0.01	0.08	0.14	0.23
Final PME	448	0.86	0.38	0.19	0.59	0.91	1.10	1.45
($\sum$ Commits)/Fund Size	448	22.76%	23.93%	0.00%	3.86%	15.75%	35.89%	69.60%
Avg. LP Commit/LP AUM	320	4.04%	11.54%	0.11%	0.42%	1.33%	3.72%	13.37%
				Panel C: U.S. Public Pension LP Characteristics				
# Pension Systems	110							
# States	46							
# CIOs	144							
As of the Commitment Year:								
LP Commit/LP Assets	1,080	0.33%	0.59%	0.05%	0.12%	0.21%	0.35%	1.09%
Reported Funding Ratio	491	78.93%	16.70%	53.66%	65.94%	80.29%	89.73%	105.76%
log(CIO Pay)	280	12.28	0.50	11.56	11.92	12.24	12.61	13.18
Board Composition:								
% Appointed	493	43.40%	33.75%	0.00%	14.29%	41.67%	69.23%	100.00%
% Elected	493	31.22%	28.78%	0.00%	0.00%	38.46%	50.00%	80.00%
% Ex-officio	493	25.38%	31.77%	0.00%	0.00%	12.50%	30.77%	100.00%
% State	493	31.28%	28.29%	0.00%	11.11%	22.22%	44.44%	100.00%
% Public	493	26.49%	24.69%	0.00%	0.00%	27.27%	42.86%	77.78%
% Plan	493	42.23%	22.96%	0.00%	28.57%	44.44%	55.56%	80.00%
% State-political	493	30.58%	28.45%	0.00%	11.11%	22.22%	42.86%	100.00%

Table 1: Tabulates summary statistics for the main variables in our study. Quarterly performance reports for each fund are net of fees and "to-date," reflecting cumulative cash flows, NAVs, or both cumulative cash flows and NAVs as of a given quarter. IRRs are annualized. The PME benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. Cambridge Associates provides the sample of funds and performance data. Preqin provides investor and commitment data. Public pension reported funding ratios are from the Public Plans Database. Pension board composition data are from Andonov, Hochberg, and Rauh (2018). CIO compensation data are from Lu, Mullally, and Ray (2021).

Table 2: Fundraising and IRRs

		Difference-in-Difference Estimates After Removing Boosting Strategies	
	Baseline	Individual	Cumulative
	(1)	(2)	(3)
$\hat{\tau}$ IRR	-0.047***		
	(-3.63)		
N	16,968		
$\hat{\tau}$ IRR - {Quick Flips}		-0.028*	
		(-1.82)	
N		11,431	
$\hat{\tau}$ IRR - {Grandstanding}		-0.042***	-0.026
		(-2.72)	(-1.60)
N		12,136	10,040
$\hat{\tau}$ IRR - {Delay Markdowns}		-0.033*	-0.011
		(-1.87)	(-0.50)
N		11,341	6,368
$\hat{\tau}$ IRR - {NAV Understatement}		-0.043**	0.014
		(-2.29)	(0.43)
N		11,336	3,981

Includes: fund FE, year-quarter FE, and controls

Table 2: Reports difference-in-differences estimates of the effect of a successful fundraising on net annualized to-date IRRs 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 IRR in the post-fundraising period, and $\hat{y}_{it}(0))$ denotes the estimated counterfactual (imputed) IRR based on the set of observations where the fund manager has not yet or never called capital for a follow-on fund. The "Baseline" column reports the estimated effect for the whole sample. The remaining columns report estimates of the effect of a successful fundraising on reported IRRs **not** attributable to several techniques that boost reported IRRs (Section 2.1.2). The "Individual" column reports the effect among funds with performance reports that are least consistent with a particular boosting technique. The "Cumulative" column reports the effect among funds with performance reports that are least consistent with any boosting technique presented in or above the one listed in the left-most row. The resulting sub-samples retain all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 3: Catering Incentives and IRR Boosting

Investor Performance Sensitivity Measure	Avg. Ratio of LP Commitments to LP AUM		Avg. Ratio of LP Commitments to LP AUM in Alt. Assets		Avg. Ratio of LP Commitments to Target LP AUM in RE Assets		Avg. Ratio of LP Commitments to LP 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	7,004	7,057	6,756	6,853	6,811	6,758

Includes: fund FE, year-quarter FE, and controls

Table 3: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by measures of investors' sensitivities to fund returns using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Investor performance sensitivity at the fund level (i) is calculated following equation (2) 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. 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 fund commitments in Preqin. The resulting sub-samples retain all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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: Catering Incentives and Return Smoothing

	NAV Return$_{it}$			
	(1)	(2)	(3)	(4)
r_t^b	0.110***	0.105***	0.120***	0.127***
	(6.40)	(6.12)	(6.72)	(7.09)
r_{t-1}^b		0.040**	0.030*	0.062***
		(2.27)	(1.75)	(3.41)
r_{t-2}^b			0.052***	0.034*
			(2.75)	(1.76)
r_{t-3}^b				0.107***
				(6.02)
Investor Performance Sensitivity$_i$ $\times r_t^b$	-0.145**	-0.125**	-0.125***	-0.109**
	(-2.52)	(-2.16)	(-2.75)	(-2.42)
Investor Performance Sensitivity$_i$ $\times r_{t-1}^b$		-0.125**	-0.125**	-0.062
		(-2.22)	(-2.15)	(-1.29)
Investor Performance Sensitivity$_i$ $\times r_{t-2}^b$			-0.005	-0.048
			(-0.05)	(-0.56)
Investor Performance Sensitivity$_i$ $\times r_{t-3}^b$				0.227***
				(3.15)
Investor Performance Sensitivity$_i$	0.028	0.031*	0.031*	0.025
	(1.59)	(1.71)	(1.73)	(1.41)
Constant	-0.115***	-0.116***	-0.117***	-0.119***
	(-4.80)	(-4.83)	(-4.86)	(-4.98)
Controls	x	x	x	x
Vintage FE	x	x	x	x
Adj R^2	0.044	0.044	0.045	0.049
N	12,501	12,501	12,501	12,501

Table 4: Regresses the quarterly returns on fund NAVs on investor performance sensitivity and quarterly benchmark returns (r^b). Regression samples include all funds where known commitments represent at least 5% of total fund commitments in Preqin. Quarterly NAV returns are winsorized at the 1% levels and are calculated as: log(NAV_{it}) - log($NAV_{i,t-1}$ - Cash Flow$_{it}$), where i indexes the fund and t indexes the quarter. Investor performance sensitivity is the average weight of the fund in its' investors' portfolios, fixed at the fund level. The benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. The unit of observation is the fund-quarter. Controls include the size of the fund, whether the GPs of the fund raised a follow-on fund, quarterly capital calls, quarterly distributions, and the cumulative percent of committed capital called as of a given quarter. 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: Determinants of Public Pension Commitments

	100 × LP Commitment/LP Assets							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% State-political	0.334***					0.407***	0.292***	0.332***
	(3.43)					(4.74)	(2.78)	(3.36)
Reported Funding Ratio		-0.622***	-0.226**			-0.207**	-0.132	-0.106
		(-3.59)	(-2.47)			(-2.34)	(-1.33)	(-1.15)
log(CIO Pay)				-0.169***	0.013	0.015		
				(-5.90)	(0.41)	(0.63)		
$\overline{\text{Prev. Commit/Assets}}$	0.267***		0.283***		0.209***	0.139**	0.267***	0.226***
	(4.88)		(5.41)		(3.60)	(2.63)	(4.94)	(4.54)
log(LP Assets)$_{t-1}$	-0.114***		-0.101***		-0.082***	-0.103***	-0.107***	-0.113***
	(-7.02)		(-5.63)		(-3.29)	(-4.96)	(-6.75)	(-7.61)
LP Performance Sensitivity($-j$)	0.052		0.053		0.051	0.048	0.052	
	(1.27)		(1.25)		(0.74)	(0.76)	(1.29)	
Constant	1.530***	0.795***	1.778***	2.336***	1.124***	1.512***	1.575***	1.799***
	(6.42)	(5.35)	(6.10)	(6.50)	(3.71)	(4.10)	(6.37)	(8.17)
Other Trustees	x					x	x	x
Controls	x		x	x	x	x	x	x
Vintage FE	x	x	x	x	x	x	x	
LP State FE	x	x	x	x	x	x	x	x
PERE Fund FE								x
Adj R^2	0.585	0.282	0.573	0.412	0.540	0.580	0.582	0.625
N	1,009	1,044	1,008	616	602	602	1,008	933

Table 5: Regresses PERE fund commitments as a percent of pension assets on pension characteristics. The unit of observation is the LP Commitment × PERE Fund. "% State-political" is the percentage of board members who are politically appointed (state-appointed and state-ex officio). Regressions including this variable also control for board percentage representation by the other types of trustees (% state-elected, % participant-elected, % participant-ex officio, % public-appointed, % public-ex officio, and % public-elected). The omitted category is % participant-appointed. Board member variable data, construction, and specifications are based on Andonov, Hochberg, and Rauh (2018). *Reported* funding ratios equal pension assets divided by pension liabilities, each of which is reported in the Public Plans Database. Plan CIO compensation (bonus plus salary) data are drawn from FOIA requests completed by Lu, Mullally, and Ray (2021). "$\overline{\text{Prev. Commit/Assets}}$" equals the average of the previous two commitments made by the pension plan scaled by the plan's assets in the year of the commitment. This number is multiplied by 100 for readability. "LP Performance Sensitivity($-j$)" equals the fund-level investor performance sensitivity for fund i calculated *excluding* the scaled commitment made by LP j (the dependent variable). Pension fund data are pooled at the system level when mapping to Preqin. Controls include the log number of previous commitments made by the pension plan, the log size of the investment board, an indicator for whether the plan has a separate board for investment and administrative decisions, the log size of the PERE fund, the total investment return of the pension the year of the commitment, and the ex-post performance of the PERE fund (TVPI, IRR, and PME). Regression samples exclude the top 1% and the bottom 1% of LP Commitments/LP Assets. Standard errors are clustered at the pension system level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 6: NAV Return Boosting and Public Pension LP Board Politicization

	NAV Return_{it}			NAV bias		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. % $\text{State-political}_{it}$	0.983**	0.954**	0.913**	1.006**	1.015**	0.955**
	(2.04)	(2.36)	(2.26)	(2.10)	(2.43)	(2.37)
Fund Timing		0.005	0.001		0.036	0.023
		(0.05)	(0.01)		(0.40)	(0.26)
Peer-Chasing		-0.142	-0.119		-0.231	-0.204
		(-0.79)	(-0.66)		(-1.23)	(-1.07)
Constant	-0.352*	-0.534	-0.615	-0.464**	-0.465	-0.564
	(-1.92)	(-0.84)	(-0.94)	(-2.55)	(-0.81)	(-0.93)
Fund FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Fund Year FE			x			x
Post-Fundraise FE			x			x
Controls		x	x		x	x
Adj R^2	0.297	0.317	0.322	0.333	0.375	0.378
N	2,415	1,954	1,953	2,443	1,980	1,979

Table 6: Regresses annual NAV returns and annual NAV bias on the average fraction of a fund's public pension LP trustees that are politically appointed as of a given year, calculated following equation (4) as:

$$\text{Avg. \% State-political}_{it} = \frac{\sum_j c_{ij} \times \text{\% State-political}_{jt}}{\sum_j c_{ij}},$$

where i indexes the PERE fund, t indexes the year of the observation, j denotes public pension LP j of fund i, c_{ij} indicates the dollar value of the capital commitment LP j made to fund i, and % $\text{State-political}_{jt}$ calculates the fraction of public pension j's board of trustees that are politically appointed in year t (which is weighted by the dollar value of LP commitments, c_{ij}). The unit of observation is the PERE fund-year. Table IA32 lists pension board composition changes in our sample. Annual NAV returns are winsorized at the 1% levels and are calculated as: $\log(NAV_{it})$ - $\log(NAV_{i,t-1}$ - Cash $\text{Flow}_{it})$. We winsorize NAV bias at the 1% levels, and calculate it as: $\log(NAV_{it})$ - $\log((1 + r_t^b) \times NAV_{i,t-1}$ - Cash $\text{Flow}_{it})$, where r_t^b denotes the annual return of the U.S. Equity REITs index (excluding mortgage REITs). Controls include annual distributions and capital calls scaled by fund size, "Fund-Timing"– the log of one plus the number of years spent without a follow-on fund exceeding two years, and "Peer Chasing"– the difference between the end-of-year IRR reported by the GPs of fund i in year $t-1$ and the median IRR reported by its peer funds in year $t-1$. Fund-timing and peer-chasing follow Brown, Gredil, and Kaplan (2019) and are further described in Table IA18. We also include the commitment-weighted pension average; reported funding ratios, the number of board trustees, and the number of LPs with board composition data available in a given PERE fund-year cell as controls. The "Fund Year" fixed effect calculates the age of the fund in years. The "Post-Fundraise" fixed effect equals one if the fund year is after the fundraising quarter and zero otherwise. 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 7: NAV Return Smoothing and Public Pension LP Board Politicization

	NAV Return$_{it}$			
	(1)	(2)	(3)	(4)
r_t^{RE}	-0.084	-0.084		
	(-0.81)	(-0.81)		
r_{t-1}^{RE}	0.299***	0.300***		
	(3.53)	(3.52)		
$r_t^{S\&P}$			0.068	0.069
			(0.40)	(0.41)
$r_{t-1}^{S\&P}$			0.253	0.254
			(1.26)	(1.26)
Avg. % State-political$_{it}$ $\times$ r_t^{RE}	0.125	0.124		
	(1.43)	(1.41)		
Avg. % State-political$_{it}$ $\times$ r_{t-1}^{RE}	0.211***	0.210***		
	(3.68)	(3.56)		
Avg. % State-political$_{it}$ $\times$ $r_t^{S\&P}$			0.203	0.201
			(1.16)	(1.12)
Avg. % State-political$_{it}$ $\times$ $r_{t-1}^{S\&P}$			0.438***	0.435***
			(3.67)	(3.44)
Avg. % State-political$_{it}$	0.859**	0.861**	0.798**	0.801**
	(3.02)	(3.00)	(3.01)	(2.98)
Constant	-0.610**	-0.614**	-0.772**	-0.777**
	(-2.27)	(-2.31)	(-2.18)	(-2.23)
Fund FE	x	x	x	x
Fund Year FE	x	x	x	x
Post-Fundraise FE		x		x
Controls	x	x	x	x
Adj R^2	0.301	0.301	0.287	0.287
N	1,953	1,953	1,953	1,953

Table 7: Regresses annual NAV returns on lagged and contemporaneous market returns interacted with the average fraction of a fund GPs' public pension trustees that are politically appointed as of a given year. We calculate this fraction following equation (4) as: Avg. % State-political$_{it}$ = $(\sum_j c_{ij} \times$ % State-political$_{jt})/(\sum_j c_{ij})$, where i indexes the PERE fund, t indexes the year of the observation, j denotes public pension LP j of fund i, c_{ij} indicates the dollar value of the capital commitment LP j made to fund i, and % State-political$_{jt}$ calculates the fraction of public pension j's board of trustees that are politically appointed in year t (which is weighted by the dollar value of LP commitments, c_{ij}). The unit of observation is the PERE fund-year, reflecting the unit of observation for board trustee data. Table IA32 lists public board composition changes in our sample. Annual NAV returns are winsorized at the 1% levels and are calculated as: log(NAV_{it}) - log($NAV_{i,t-1}$ - Cash Flow$_{it}$). For year t, r_t^{RE} denotes the return of the FTSE Nareit U.S. Equity REITs index (which excludes mortgage REITs), and $r_t^{S\&P}$ denotes the value-weighted S&P 500 return. Controls and fixed effect definitions are the same as in Table 6. Standard errors are clustered at the year level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 8: Catering Incentives, IRR Boosting, and Investor Characteristics

Investor Performance Sensitivity Measure	Avg. Ratio of LP Commitments to LP AUM		Avg. Ratio of LP Commitments to LP AUM in Alt. Assets		Avg. Ratio of LP Commitments to Target LP AUM in RE Assets		Avg. Ratio of LP Commitments to LP AUM in Private RE Assets	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Past LP 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
Average # 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
Average # of Previous PERE Investments								
High	-0.050**	-0.020	-0.039*	-0.026	-0.063**	-0.015	-0.031	-0.025
	(-2.39)	(-0.96)	(-1.75)	(-1.28)	(-2.45)	(-0.72)	(-1.22)	(-1.30)
N	3,606	5,160	3,718	4,968	3,289	5,082	3,601	4,635
Low	-0.061***	-0.002	-0.059***	-0.002	-0.059***	0.000	-0.063***	0.007
	(-3.97)	(-0.09)	(-3.38)	(-0.08)	(-3.92)	(0.01)	(-3.83)	(0.33)
N	4,542	3,255	4,497	3,300	4,678	2,982	4,421	3,334

All specifications include: fund FE, year-quarter 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 aggregated to the fund level using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. High versus low classifications are always assigned using the full sample of funds, so for example, whether a fund is classified as having better-performing LPs is *not* conditioned on whether the GP faces high or low catering incentives. The resulting sub-samples keep all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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: Catering Incentives, IRR Boosting, and Fund Characteristics

Investor Performance Sensitivity Measure	Avg. Ratio of LP Commitments to LP AUM		Avg. Ratio of LP Commitments to LP AUM in Alt. Assets		Avg. Ratio of LP Commitments to Target LP AUM in RE Assets		Avg. Ratio of LP Commitments to LP 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 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
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

All specifications include: fund FE, year-quarter 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. High versus low classifications are always assigned using the full sample of funds, so for example, whether a fund is classified as having a high reputation GP is *not* conditioned on whether the GP faces high or low catering incentives. The resulting sub-samples keep all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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

Table A1: Techniques to Boost IRRs

Quick Flips: Quick-flips involve exiting better investments earlier, thereby holding worse investments longer. We flag funds as consistent with executing quick flip investments if they are (i) in the top tercile of average scaled distributions per year during fundraising or (ii) once the fund's RVPI < .05. This technique is related to Phalippou (2008) and Lopez-de-Silanes, Phalippou, and Gottschalg (2015).

Grandstanding: Grandstanding involves making large distributions before fundraising to boost reported performance. We flag funds as consistent with grandstanding if they are in the top tercile of DPI growth the year before fundraising. This technique is related to Gompers (1996).

Delay Markdowns: Delaying markdowns involves waiting until after fundraising to reveal bad investments– thereby maintaining a higher IRR. We flag funds as consistent with delaying markdowns if they are in the top tercile of markdowns the year after fundraising. This technique is related to Barber and Yasuda (2017) and Chakraborty and Ewens (2018).

NAV Overstatement: Overstating NAVs involves aggressively marking up the value of fund investments– thereby boosting reported IRRs. These tests are presented in Table IA15, using a continuous measure that flags funds as overstating NAVs if the average NAV bias (the returns to NAVs not explained by cash flows or market returns) over the year before the fundraising quarter is in the top X% (e.g., 33%) of all NAV bias measurements for the year before fundraising, measured in event time. This technique is related to Brown, Gredil, and Kaplan (2019).

NAV Understatement: Understating NAVs involves conservatively measuring the value of fund investments. By itself, understating NAVs does not boost reported IRRs. However, fund managers can make their IRRs "pop" by understating NAVs if they subsequently exit the underlying investments at a higher market price than the one included in the IRR calculation. We flag a fund as understating NAVs if the average NAV bias (the returns to NAVs not explained by cash flows or market returns) over the year before the fundraising quarter is in the bottom tercile of all NAV bias measurements for the year before fundraising, measured in event time. This technique is related to Brown, Gredil, and Kaplan (2019).

Table A1: Describes several techniques by which GPs could boost fund-level net-of-fee IRRs and how we "flag" these techniques.

Internet Appendix for: Catering and Return Manipulation in Private Equity

August 18, 2023

IA.1 Cash Flow and Net Asset Value Imputations

In this section, we present the imputations used to impute quarterly cash flows and NAVs throughout our paper. PE performance metrics are functions of PE cash flows and underlying portfolio investment valuations, and can be rearranged to calculate the cash flows and NAVs that correspond to each quarterly report. Andonov, Kräussl, and Rauh (2021) employ a similar procedure.

We impute three cash-flow variables; quarterly calls from LPs, quarterly distributions to LPs, and quarterly net asset values. 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:

$$C_{it} = F_i \times (PC_{it} - PC_{i,t-1}), \tag{IA1}$$

where F_i denotes the size of the fund. Equation (IA1) recovers the level of capital called in quarter t if the total amount 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 the fund size. One 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. We find this produces similar cash-flow profiles to those reported 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. Similar cash-flow patterns also attain 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:

$$D_{it} = F_i \times (DPI_{it} \times PC_{it} - DPI_{i,t-1} \times PC_{i,t-1}). \tag{IA2}$$

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 NAVs by converting the residual value to paid-in capital (RVPI) to a dollar amount:

$$NAV_{it} = F_i \times PC_{it} \times \underbrace{(TVPI_{it} - DPI_{it})}_{RVPI_{it}}. \tag{IA3}$$

Table IA2 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. Figure IA1 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 indicates that the two are similar.

IA.2 Commitment Data Imputations

The Preqin commitment data are missing the dollar value of commitments for some known LPs and the dollar value of commitments for unknown LPs. The true quantity of LPs is also unknown. In this section, we discuss our method for estimating the number of LPs, and corresponding commitments made by each LP, in each fund. We rely on these imputations for our main cross-sectional specifications, but also ensure our cross-sectional results are not driven by imputed values. Specifically, our main results are similar (and slightly stronger in some cases) if we repeat cross-sectional tests without making these imputations (i.e., Table IA25).

To start, we decompose the observed fund size into (i) the sum of known commitments made by known LPs, (ii) the sum of unknown commitments made by known LPs, and (iii) the sum of unknown commitments made by unknown LPs:

$$F = \underbrace{\sum_{j=1}^{j=L^N} c_j}_{\text{Observed \$ Values}} + \underbrace{\sum_{k=1}^{k=L^Q} c_q}_{\text{Missing \$ Values}} + \underbrace{\sum_{k=L^Q+1}^{k=L^Q+L^M+1} c_q}_{\text{Missing \$ Values \& LPs}}, \tag{IA4}$$

where the fund of size F has L^N commitments with known dollar values (c_j), L^Q commitments where the LPs are known but the dollar value of the commitments are not known, and L^M commitments where both the LPs and the dollar value of the commitments could be missing. For example, we may view that the GPs of a fund raised \$100 in capital from 10 LPs, where 8/10 LPs report that they made commitments totaling \$80. Our procedure assigns the residual \$20 to the remaining two LPs ($L^Q = 2$) accounting for the fact that some LPs are not reported in Preqin (if $L^M > 0$).

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 $a(c_j)$. 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:

$$\tilde{F} = \sum_{j=1}^{j=L^N} c_j + (L^K \times a(c_j)), \tag{IA5}$$

where every quantity in equation (IA5) 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 estimate 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*) can be expressed as:

$$(c_q, L^M) = \begin{cases} \left(a(c_j), \dfrac{F}{a(c_j)} - L^N \right), & \text{if } \tilde{F} < F, \\ \\ \left(\dfrac{F - \sum_{j=1}^{j=L^N} c_j}{L^Q}, 0 \right), & \text{if } \tilde{F} \geq F \end{cases} . \tag{IA6}$$

We illustrate our procedure with three examples, each of which assumes the GPs of the fund raised \$100 in capital and 10 LPs are reported for the fund in Preqin.

1. **The value of commitments for 8/10 LPs is available, summing to \$ 80.** The average known commitment is \$10 (= 80/8). In step one of our procedure, we assume there are no missing LPs and that the remaining two LPs made commitments equal to the average of \$10. Under this assumption, the estimated fund size equals \$100 (=\$80 (known) + (10-8)×\$10 (missing)). The estimated fund size equals the actual fund size and our procedure stops; we estimate zero missing LPs and that the missing commitments each equal \$10.

2. **The value of commitments for 8/10 LPs is available, summing to \$ 40.** The average known commitment is \$5 (= 40/8). In step one of our procedure, we assume there are no missing LPs and that the remaining two LPs made commitments equal to the average of \$5. Under this assumption, the estimated fund size equals \$90 (=\$40 (known) + (10-8)×\$5 (missing)). The estimated fund size is below the actual fund size and our procedure continues to step #2. We assume that the remaining LPs each make an average commitment of \$5, meaning that 12 LPs are needed to account for the missing \$60 of commitments, two of which are known and 10 of which are assumed to be missing from Preqin.

3. **The value of commitments for 8/10 LPs is available, summing to \$ 96.** The average known commitment is \$12 (= 96/8). In step one of our procedure, we assume there are no missing LPs and that the remaining two LPs made commitments equal to the average of \$12. Under this assumption, the estimated fund size equals \$120 (=\$96 (known) + (10-8)×\$12 (missing)). The estimated fund size is above the actual fund size and our procedure continues to step #2. We assume that no extra LPs are needed to account for the missing \$4 of commitments but instead that the missing LPs made commitments below the average level of the known commitments. We assume each the \$4 of unaccounted for commitments is shared equally by the two known LPs with missing commitments, meaning that we impute the missing two commitments to be \$2 each (=\$4/2) and that all LPs are accounted for in Preqin.

We simulate the commitment data for $10,000$ funds (indexed by i) to provide a validation of our estimation. We first assign a "true" number of LPs $\sim Uniform_i[2, 100]$ for each fund i, allowing each

LP$_j$ of fund i to make a commitment $\sim Uniform_j[\$5, \$100]$. We then approximate the data provided by Preqin by randomly allowing only some of the total number of LPs ($\sim Uniform_i[2, 100]$) of a fund to be observable. We further allow only the commitments of a fraction of known LPs to be observable ($\sim Uniform_i[2, \#LPs$ assigned to fund $i]$). Lastly, we allow ourselves to view only some fraction, $\alpha_i \in (0, 1]$, of the commitments made by the observable LPs in each fund. As a simplified example, we could assign a fund to have three LPs, each making a commitment of \$50, implying a total fund size of \$150. Our filters could allow (i) only two/three LPs to be available and only (ii) one/two \$50 commitments made by known LPs to be viewable. With our simulated data, we then estimate the number of LPs and the value of their commitments in each fund using the method summarized by equation (IA6).

Table IA3 summarizes our simulation results. 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 0.12. In contrast, the correlation between HHI using the simulated true data and our imputation procedure is 0.95. Additionally, the correlation between the number of LPs using the simulated true data and the known commitments is only 0.59 but increases to 0.99 after applying our imputation procedure. These results indicate that our estimation improves the quality of our HHI and LP counts in our simulated setting.

A potential concern with our procedure is that the average of known commitments may not fully represent the commitments made by LPs that are either (a) not in the database or (b) known to have made commitments where the values of the commitments are not known. Non-representative averages can lead to inflated numbers of missing LPs and deflated average commitment values. For example, consider a case where the GPs of the fund raised \$100 in capital, with 10 reported LPs, and one known commitment of \$0.25. Our procedure would unconditionally imply that this fund's commitments are represented by a total of 400 LPs, each committing \$0.25– an estimated number of LPs that is likely too large, and an average commitment that is likely too small. To address this concern, we restrict our sample to only 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, as implied by our algorithm.

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Figure IA1: Imputed and Actual IRRs

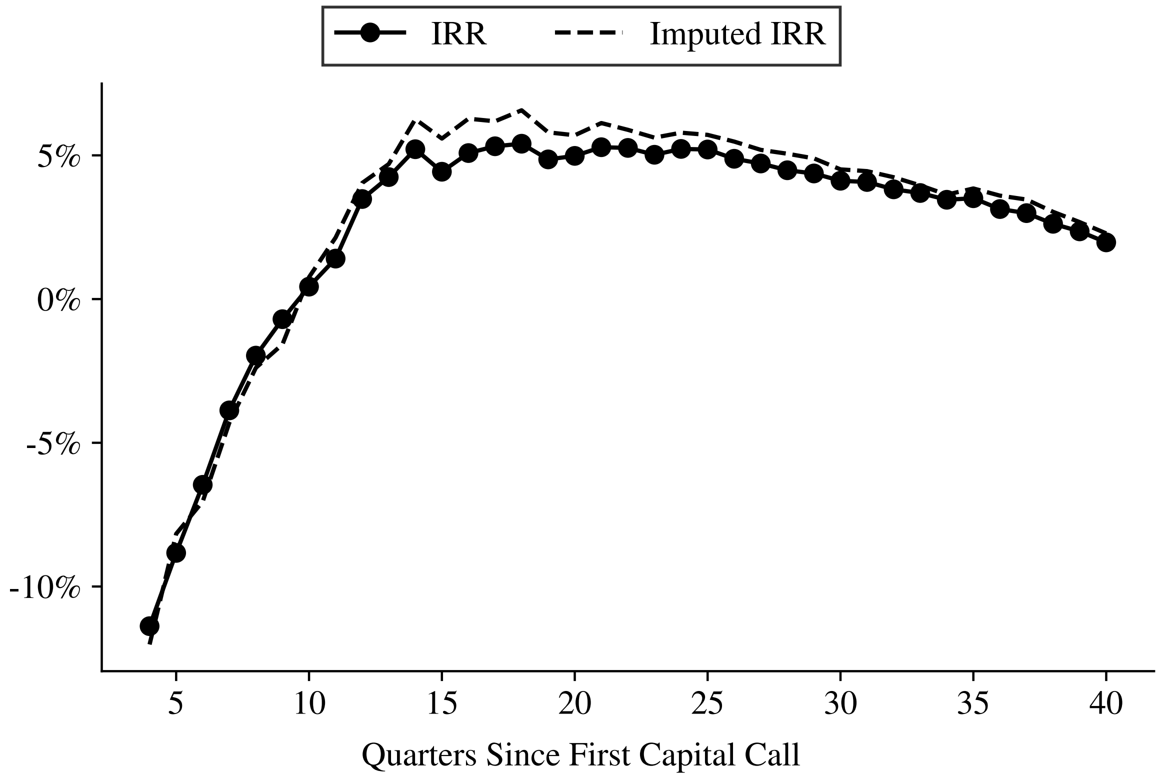

Figure IA1: Plots the average *reported* and *imputed* net IRRs since the first capital call for the 448 funds in our sample. Imputed IRRs are calculated using imputed cash-flows and net asset values derived in Section IA.1. Imputed and actual IRRs greater than 100% are excluded. The plot includes quarters 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.

Figure IA2: Sample Composition by Fundraising Status

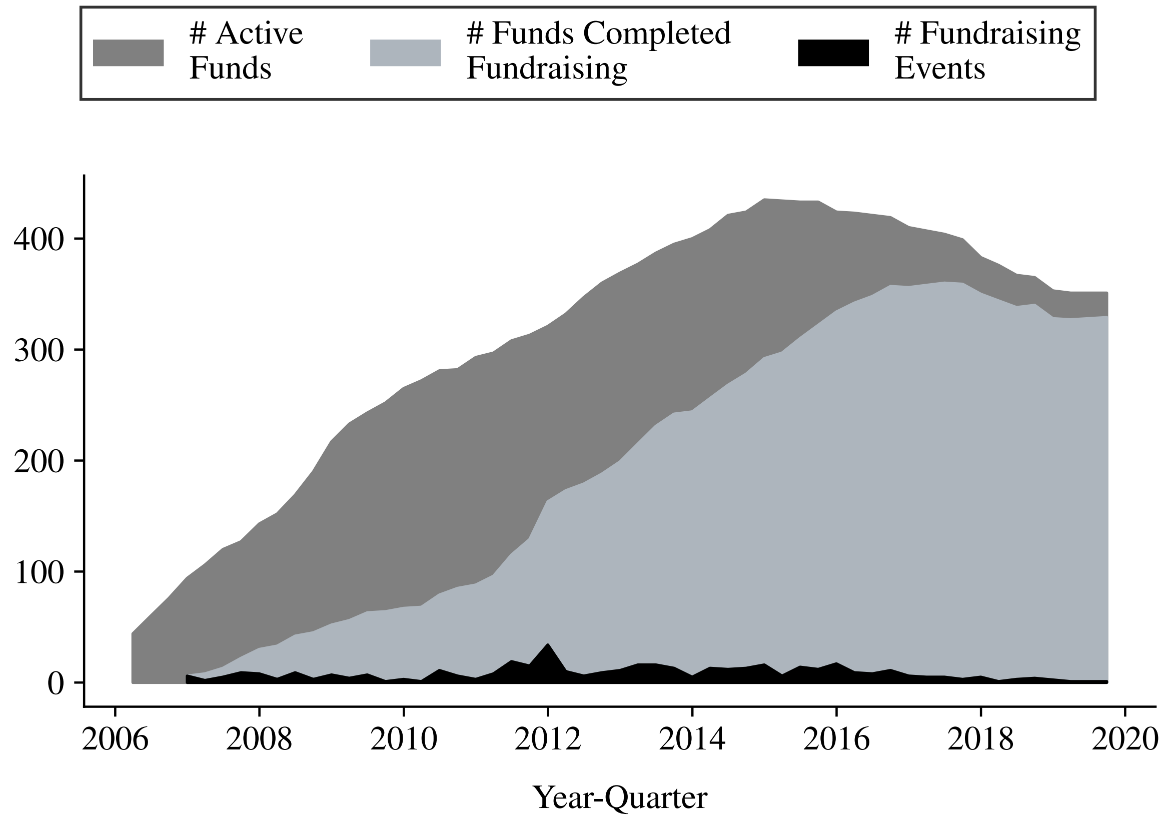

Figure IA2: Plots the number of funds in each year-quarter in our sample where the GP reports IRR and (a) has not called capital for a successor fund, (b) has called capital for a follow-on fund, or (c) makes the first capital call for a follow-on fund. Throughout, we interpret the first capital call of the follow-on fund as marking the completion of fundraising, following Barber and Yasuda (2017) and Brown, Gredil, and Kaplan (2019). The plot is smoothed by a lowess function with a smoothing weight of 0.20.

Figure IA3: Distribution of Fundraising Events

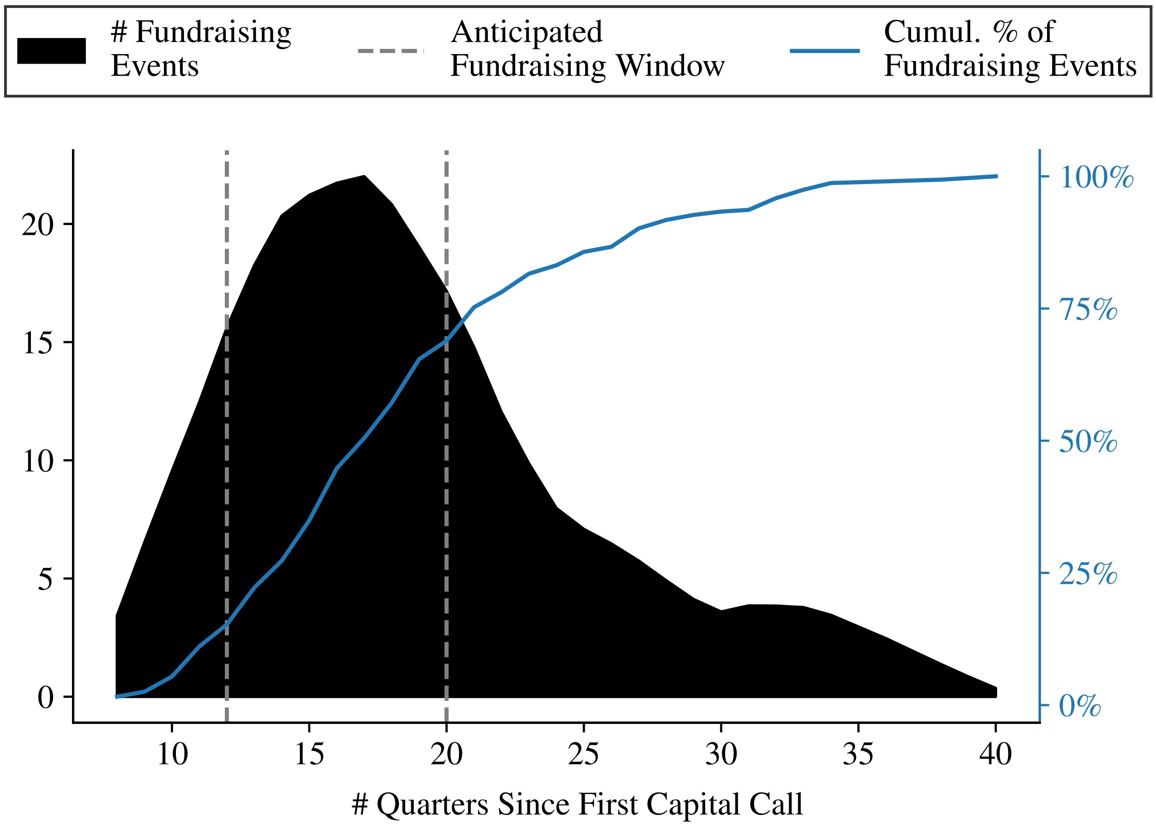

Figure IA3: Plots the distribution of fundraising events since a fund's first capital call for 315 out of 448 funds in our sample where (i) the GPs successfully raised capital for a follow-on fund before quarter 40, and (ii) we observe the precise quarter of the successor fund's first capital call. (The plot is similar if it includes all 416/448 funds where the GPs successfully raised a follow-on fund.) The distribution is smoothed by a lowess function with a smoothing weight of 0.30. The plot includes quarters 8 through 40 in the fund's life. The vertical lines denote years 3-5, where PE participants typically expect a fundraising event to occur. The blue line (right axis) plots the cumulative fraction of fundraising events that have taken place 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. 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.

Figure IA4: Placebo Tests

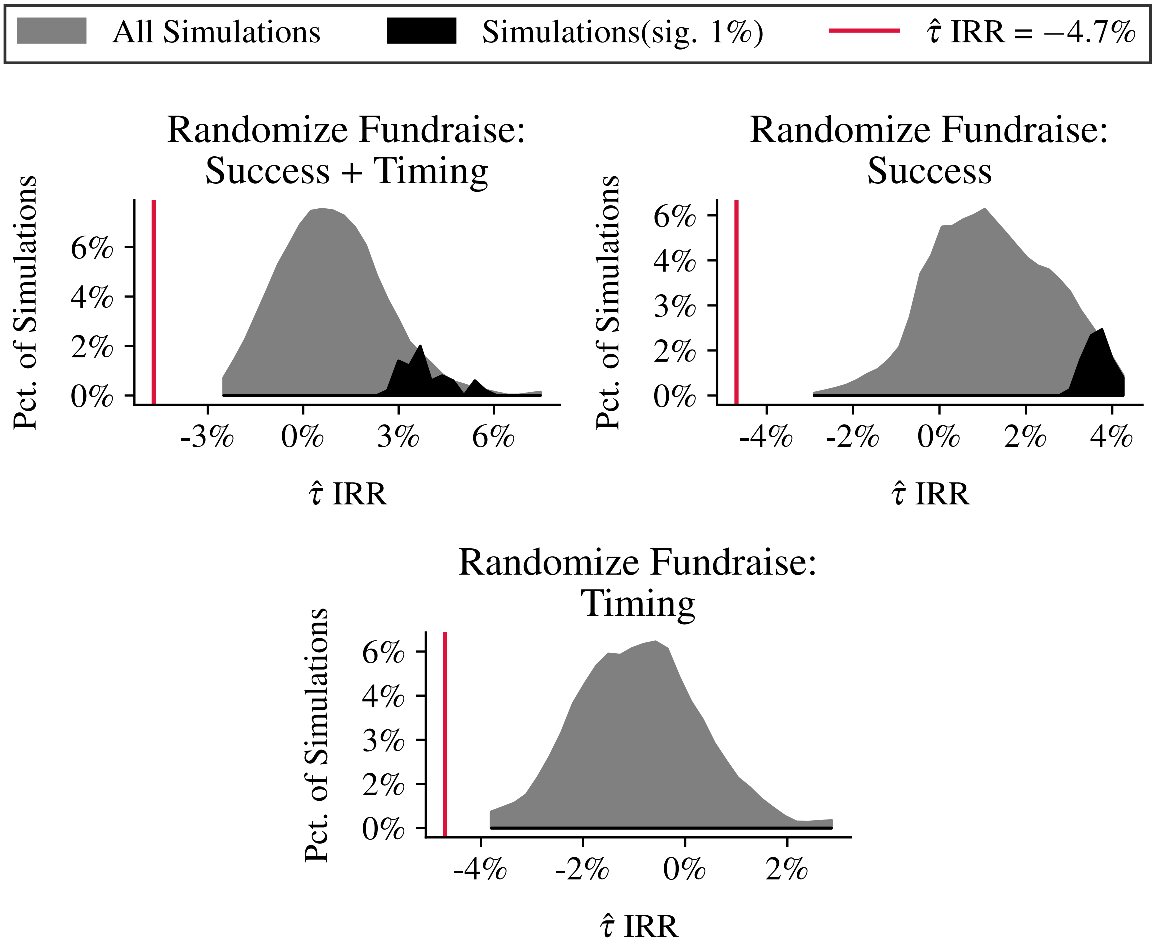

Figure IA4: Plots the distribution of the estimated effect of fundraising on IRRs ($\hat{\tau}$ IRR) under various placebo specifications, each simulated 500 times, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. Panel titles indicate whether (i) fundraise timing, (ii) fundraise success, or (iii) both fundraise timing and fundraise success were randomized before estimating the effect of fundraising on IRRs within a given draw of the simulation. The shaded black areas denote all simulation draws for which the estimated treatment effect was statistically significant at the 1% level. Distributions are smoothed by a lowess function with a smoothing weight of 0.20. The red vertical line plots the estimated treatment effect using correct (non-randomized) fundraising outcomes and timings. All specifications include fund and year-quarter fixed effects, and one quarter lags of PME and NAV as controls. Standard errors are clustered at the fund level.

Figure IA5: Fund NAVs and Cash Flows in Event Time

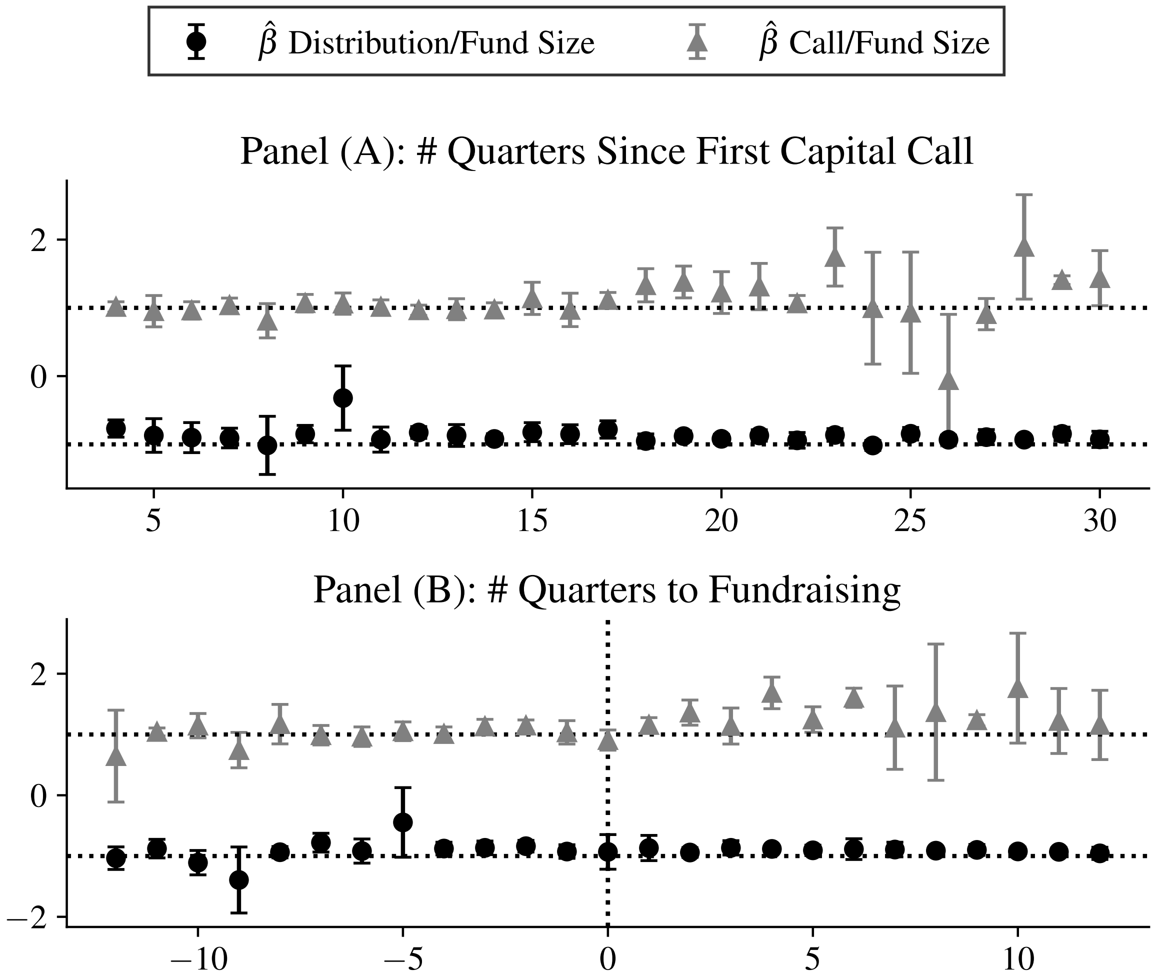

Figure IA5: Plots estimated regression coefficients $\{\beta_1, \beta_2\}$ from regressions in event time of the form: $\Delta NAV_{it} = \beta_1 \text{Distribution}_{it}/\text{Fund Size}_i + \beta_2 \text{Call}_{it}/\text{Fund Size}_i + \lambda_t + e_{it}$, where i indexes the fund, t indexes the time (measured in year-quarters), and λ_t denotes a year-quarter fixed effect. ΔNAV_{it} equals NAV_{it} - $\text{NAV}_{i,t-1}$. Panel A plots coefficients from regressions conducted within each quarter since the fund makes its' first capital call. Panel B plots coefficients from regressions conducted within each quarter around the fundraising quarter (the first capital call for fund #N+1). Circles correspond to coefficients for the distribution term (β_1). Triangles correspond to coefficients for the call term (β_2). Standard errors are clustered in calendar time. Vertical lines denote 95% confidence intervals. Horizontal lines equal the null hypotheses of one for calls or negative one for distributions.

Figure IA6: Rolling NAV Volatility

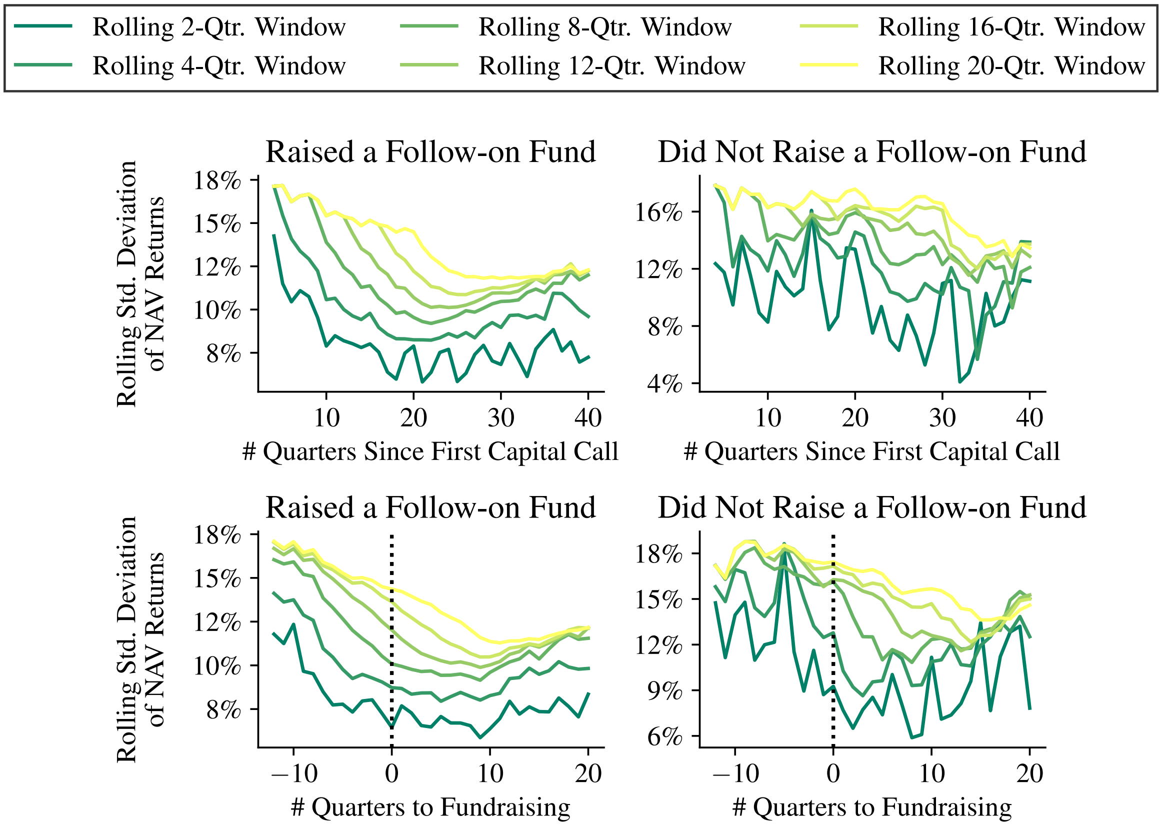

Figure IA6: Plots the average (within-fund) rolling volatility of NAV returns, separately among funds where the GPs successfully raised capital for a follow-on fund ("successful fundraisers") and where the GPs failed to raise capital for a follow-on fund ("unsuccessful fundraisers"). Rolling volatility calculations require at least two fund-quarter observations. The vertical black dotted lines plot the fundraising event. In the second cell of the second column, pseudo-fundraising quarters for unsuccessful fundraisers equal the median time to raise capital for a follow-on fund for other funds where the GPs successfully raised capital for a follow-on fund with the same vintage year.

Figure IA7: Catering Incentives and Return Smoothing with More Lags

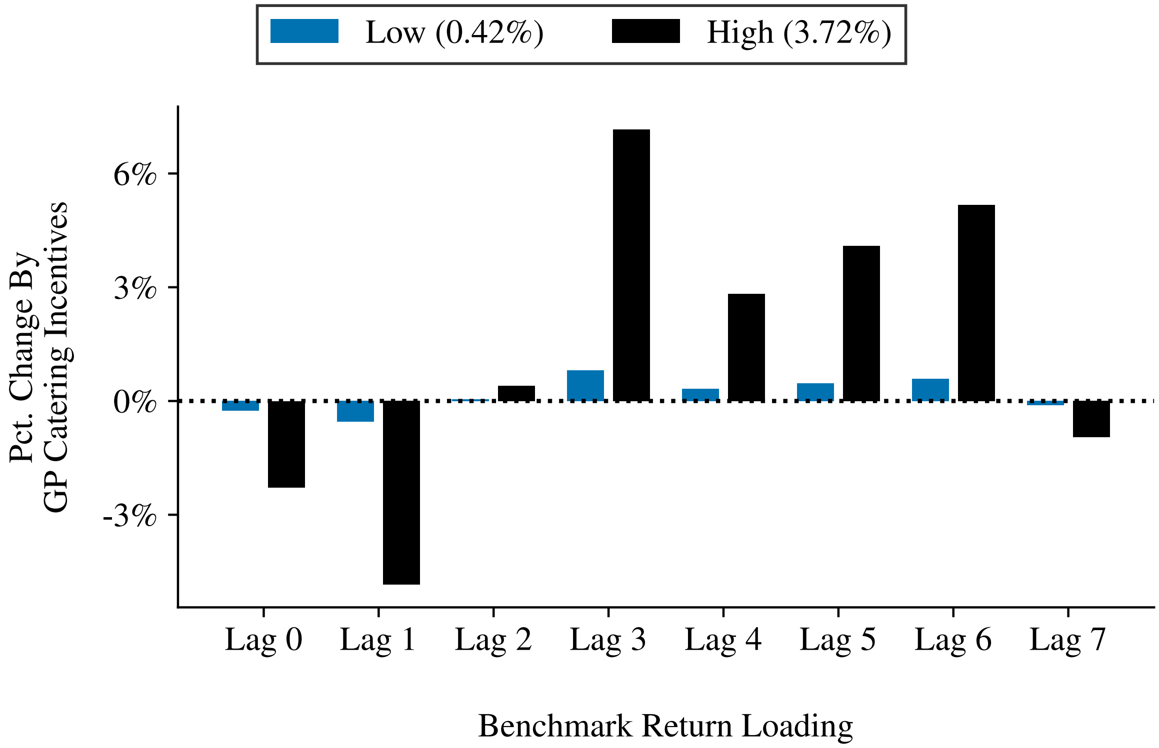

Figure IA7: Plots the percentage change in contemporaneous and lagged benchmark return loadings after varying the level of investor performance sensitivity to be 0.42% or 3.72%– the 25$^{\text{th}}$ and the 75$^{\text{th}}$ percentiles of investor performance sensitivity, respectively. Benchmark return loadings are obtained from the regression: $r_{it}^{NAV} = \sum_{k=0}^{k=7} \lambda_k r_{t-k}^{b} + \beta_k(\text{IPS}_i \times r_{t-k}^{b}) + \gamma \text{IPS}_i + \delta X' + \psi_i + e_{it}$, where i indexes the fund, t indexes the year quarter of the observation, r_{it}^{NAV} equals the quarterly NAV return of a fund accounting for quarterly cash flows, IPS_i is shorthand for investor performance sensitivity (our main measure of catering incentives; equation (2)), r_{t-k}^{b} denotes quarterly benchmark returns lagged by k quarter(s), X' denotes a vector of controls (including quarterly cash flows, fund size, and whether the GPs of the fund ultimately raised capital for a follow-on fund), and ψ_i denotes a vintage year fixed effect. Bars in the plot equal $\text{IPS}_i \times \beta_k/\lambda_k$, where k denotes the applicable lag, using the results from the regression of NAV returns on benchmark returns.

Figure IA8: Return Smoothing and Aggregate PERE Commitments

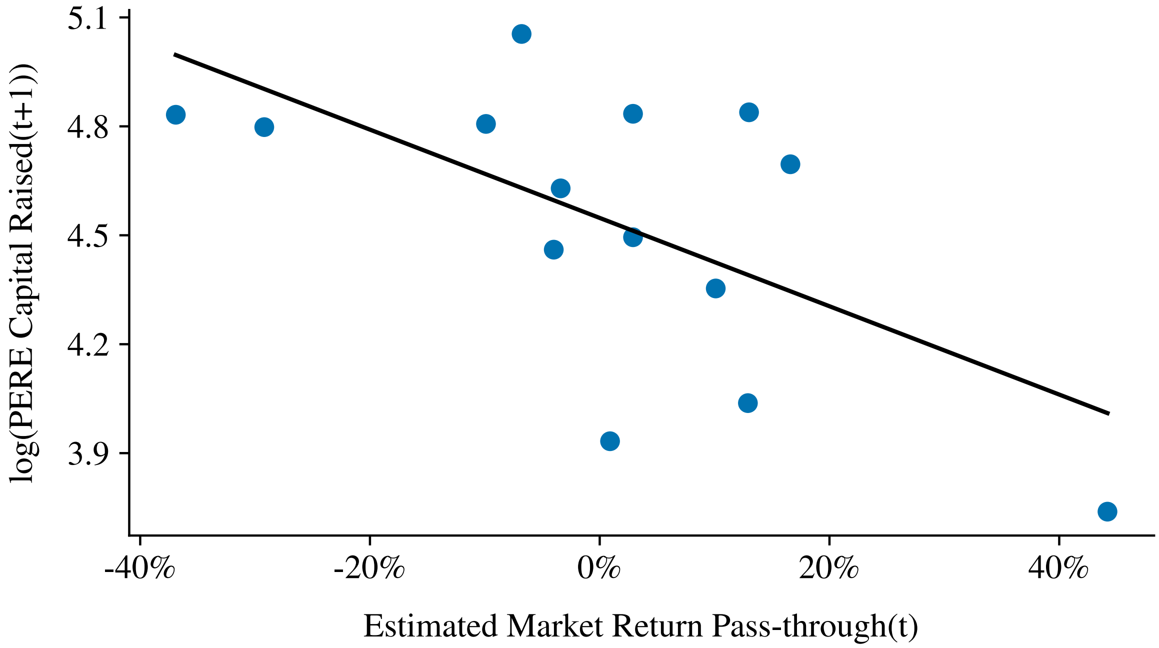

Figure IA8: Plots the relationship between the estimated market return "pass-through" to PERE NAV returns in a given year (t) and aggregate commitments to PERE funds (in \$Billions) in the following year ($t + 1$). Market pass-throughs are estimated from year-by-year regressions of quarterly returns to fund NAVs on quarterly benchmark returns. Funds stop entering the panel in 2014. Table IA31 presents the results of these regressions. The benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. Aggregate PERE commitments are obtained from Preqin, equaling the sum of all capital raised by opportunistic, distressed, value-added, core, and core-plus funds in a given vintage year. The solid black line plots a regression fitted to these data.

Table IA1: Sample Composition by Vintage Years

Vintage Years:	2001 - 2003	2004 - 2006	2007 - 2009	2010 - 2014	All
			Panel A: Fund Composition		
# Firms	25	109	118	113	208
# Funds	28	147	141	132	448
% First Time Fund	17.9%	23.8%	17.0%	15.2%	18.8%
Strategy:					
Opportunistic	35.7%	46.9%	51.1%	41.7%	46.0%
Value Added	53.6%	45.6%	41.1%	41.7%	43.5%
Core-Plus	10.7%	4.8%	4.3%	8.3%	6.0%
Distressed	0.0%	0.7%	2.8%	6.1%	2.9%
Core	0.0%	2.0%	0.7%	2.3%	1.6%
Geographic Focus:					
North America	92.9%	67.3%	57.4%	68.2%	66.1%
Europe	3.6%	15.6%	19.1%	13.6%	15.4%
Asia	3.6%	15.6%	18.4%	9.8%	14.1%
Rest of World	0.0%	1.4%	5.0%	8.3%	4.5%
Main Property Type:					
Diversified	78.6%	76.9%	77.3%	70.5%	75.2%
Office	14.3%	7.5%	5.0%	6.1%	6.7%
Residential	0.0%	4.8%	5.0%	11.4%	6.5%
Industrial	3.6%	2.7%	4.3%	3.8%	3.6%
Retail	3.6%	2.0%	5.0%	2.3%	3.1%
Niche	0.0%	2.7%	2.1%	5.3%	3.1%
Hotels	0.0%	3.4%	1.4%	0.8%	1.8%
			Panel B: Commitment Composition		
# Funds	27	139	136	121	423
# LPs	234	711	822	745	1374
# Commits	346	2027	2000	1548	5921
% Has $ Value	30.9%	35.3%	32.7%	31.2%	33.1%
% FOIA Sourced	32.4%	31.0%	29.1%	28.2%	29.7%
Commitment Source by LP Type:					
% North American	98.3%	93.1%	90.9%	92.2%	92.4%
% Public Pension	32.4%	26.4%	28.4%	29.9%	28.3%
% Private Sector Pension	27.2%	26.0%	26.3%	31.7%	27.6%
% Foundation	24.3%	17.8%	18.1%	16.3%	17.9%
% Endowment	8.1%	14.4%	12.3%	10.4%	12.3%
% Insurance Company	2.3%	6.0%	5.7%	4.9%	5.4%
% Asset Manager	2.3%	3.2%	2.8%	1.4%	2.5%
% Other	3.5%	6.2%	6.6%	5.4%	6.0%

Table IA1: Tabulates the composition of PERE funds and LP capital commitments in our sample by vintage year cohorts. The sample of funds is from Cambridge Associates. Preqin provides investor and commitment data.

Table IA2: Cash Flow Imputation Example

	Observed Performance Metrics				Imputed Cash Flows & NAVs		
Quarters Since First Capital Call	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

Table IA2: Tabulates the quarterly cash-flow and NAV imputations for a hypothetical fund of size \$100 with 15 quarters of data. This table assumes that calls, distributions, and NAVs are missing but imputed using the observed performance metrics.

Table IA3: Correlations Between Simulated and Imputed LP Profiles

		HHI			# LPs	
		Actual	Available Data	Imputed	Actual	Available Data
HHI	Actual	1.00				
	Available Data	0.12	1.00			
	Imputed	**0.95**	0.16	1.00		
# LPs	Actual	-0.61	-0.24	-0.62	1.00	
	Available Data	-0.40	0.39	-0.40	0.59	1.00
	Imputed	-0.60	-0.25	-0.62	**0.99**	0.58

Table IA3: Tabulates correlations between LP counts and commitment dispersions for a randomly created sample of funds following Section IA.2. Bold correlation coefficients denote the outcomes of our imputation procedure.

Table IA4: Example Successor Fund Provisions

Example A: "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: Institutional Limited Partners Association (ILPA) Model Terms 2020: Section 9.1, https://bit.ly/3DEIfyQ*

Example B: "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." *Source: "Successor Funds and the Problems with PPM Triggers," Chrisopher Schelling for Buyouts Insider (2016), https://bit.ly/3qW4FGC*

Example C: "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: "Successor Funds and the Problems with PPM Triggers," Chrisopher Schelling for Buyouts Insider (2016), https://bit.ly/3qW4FGC*

Table IA4: Transcribes language seen in Limited Partnership Agreements, fund governance documents, that create limitations for when general partners can raise successor funds.

Table IA5: IRRs and Predicted Fundraising Events

Predict Fundraising Events by:	(1) 3 Years	(2) 4 Years	(3) 5 Years	(4) $66.\overline{66}$% Called	(5) 75% Called	(6) Industry Avg.
$\hat{\tau}$ IRR	-0.056***	-0.065***	-0.051***	-0.047**	-0.047**	-0.118***
	(-3.12)	(-4.88)	(-4.66)	(-2.00)	(-2.10)	(-5.37)
Year-Qtr. FE	x	x	x	x	x	x
Fund FE	x	x	x	x	x	x
$\text{PME}_{i,t-1}$	x	x	x	x	x	x
$\text{NAV}_{i,t-1}$	x	x	x	x	x	x
N	16,968	16,968	16,968	14,441	14,553	10,063

Table IA5: Tabulates the effect of a *predicted* fundraising event on reported IRRs using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator, where the timing of fundraising events are predicted assuming they occur according to boilerplate LPA terms or industry norms. Columns 1-3 assume fundraising events occur at years three, four, or five in a fund's life. Columns 4 and 5 assume fundraising events occur once the GP calls a fixed percent of committed capital. These predicted fundraising dates reflect the expiration of boilerplate successor fund provisions, assuming the terms are common across all funds in our sample. Column 6 assumes fundraising events occur according to the industry average time between funds. The average time between funds equals the average difference between vintage years of successive funds (with vintages at least three years apart) within a series of funds with the same strategy within a PERE firm. For vintage year v and a gap between successive funds of g, the industry average is the average of all gaps for funds with vintages less than $v - g$ (to avoid any forward contamination). The industry average calculation uses all core, core-plus, opportunistic, value-added, and distressed PERE funds in Preqin with a known size, manager, and vintage. The industry average time between PERE funds within a firm (still exceeding three years) has been about 3.5 years since 2000, with little variation. The regression sample in column 6 excludes funds where the GP successfully raised capital for a follow-on fund but the industry average for the fund-strategy-vintage cell could not be calculated due to missing data. In our main specifications (e.g., Table 2), we instead use the actual timing of fundraising events when estimating our DiD results. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA6: Placebo Tests

Randomly Vary:	Parameter	# Simulations	Mean	Std. Dev.	5%	25%	50%	75%	95%
Fundraise Success + Timing	$\hat{\tau}$ IRR	500	0.01	0.02	-0.01	0.00	0.01	0.02	0.04
	t-stat.	500	0.86	1.20	-1.17	0.00	0.90	1.72	2.86
	$\hat{\tau}$ IRR(1% sig.)	38	0.04	0.01	0.03	0.04	0.04	0.04	0.06
Fundraise Success	$\hat{\tau}$ IRR	500	0.01	0.01	-0.01	0.01	0.01	0.02	0.04
	t-stat.	500	1.06	1.00	-0.55	0.34	1.07	1.73	2.68
	$\hat{\tau}$ IRR(1% sig.)	37	0.04	0.00	0.03	0.04	0.04	0.04	0.04
Fundraise Timing	$\hat{\tau}$ IRR	500	-0.01	0.01	-0.03	-0.02	-0.01	0.00	0.01
	t-stat.	500	-0.69	0.97	-2.31	-1.36	-0.61	-0.03	0.85
	$\hat{\tau}$ IRR(1% sig.)	18	-0.03	0.00	-0.04	-0.03	-0.03	-0.03	-0.03

Table IA6: Tabulates the distribution of the estimated effect of fundraising on IRRs ($\hat{\tau}$ IRR) and accompanying test-statistics (t-stat.) under various placebo specifications, each simulated 500 times, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. Results are grouped by whether (i) fundraise timing, (ii) fundraise success, or (iii) both fundraise timing and fundraise success were randomized before estimating the effect of fundraising on IRRs within a given draw of the simulation. The row titled "$\hat{\tau}$ IRR(1% sig.)" tabulates the distribution of estimated treatment effects where the simulation draw resulted in a statistically significant estimate at the 1% level. All specifications include fund and year-quarter fixed effects, and one quarter lags of PME and NAV as controls. Standard errors are clustered at the fund level.

Table IA7: 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
$PME_{i,t-1}$	x	x	x
$NAV_{i,t-1}$	x	x	x
N	16,968	16,968	16,968

Table IA7: 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 year-quarter fixed effects, and one quarter lags of 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 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
$\text{PME}_{i,t-1}$		x				
$\text{NAV}_{i,t-1}$		x	x		x	x
$\text{DPI}_{i,t-1}$			x			
$\text{IRR}_{i,t-1}$				x	x	
$\text{TVPI}_{i,t-1}$						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 specifications use fund and year-quarter 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: Shifting Fundraising Dates

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

Table IA9: 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 year-quarter fixed effects, and one quarter lags of 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 IA10: Annual Panels

Quarter:	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$\hat{\tau}$ IRR	-0.050*** (-3.53)	-0.046*** (-3.38)	-0.043*** (-3.40)	-0.048*** (-2.79)
Year FE	x	x	x	x
Fund FE	x	x	x	x
$\text{PME}_{i,t-1}$	x	x	x	x
$\text{NAV}_{i,t-1}$	x	x	x	x
N	4,084	4,310	4,370	4,044

Table IA10: Tabulates the effect of a successful fundraising on IRRs as if IRRs are only viewed once per year rather than once per quarter. For example, the "Q1" column 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 year fixed effects, and one quarter lags of 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 IA11: 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**	-0.029***	-0.028**
	(-3.62)	(-3.72)	(-2.57)	(-2.58)	(-2.41)
Year-Qtr. FE	x	x	x	x	x
Fund FE	x	x	x	x	x
$\text{PME}_{i,t-1}$	x	x	x	x	x
$\text{NAV}_{i,t-1}$	x	x	x	x	x
N	16,966	15,951	14,159	13,142	13,960

Table IA11: 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 unsuccessful fundraisers. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA12: Alternate Weights for Unsuccessful Fundraisers

	(1)	(2)	(3)	(4)	(5)	(6)
Oversample %:	60	65	70	75	80	85
$\hat{\tau}$ IRR	-0.037***	-0.038***	-0.030***	-0.039***	-0.058***	-0.038***
	(-3.53)	(-3.74)	(-2.73)	(-3.29)	(-5.23)	(-3.01)
Year-Qtr. FE	x	x	x	x	x	x
Fund FE	x	x	x	x	x	x
$\text{PME}_{i,t-1}$	x	x	x	x	x	x
$\text{NAV}_{i,t-1}$	x	x	x	x	x	x
N	26,372	24,312	22,323	20,969	19,742	18,571

Table IA12: Tabulates the effect of a successful fundraising on quarterly performance metrics, after overweighting the unsuccessful fundraisers, using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. For example, in the 60% column, unsuccessful fundraisers are resampled (with replacement) until the fundraising success rate for all funds in the panel equals 60%. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA13: IRRs and Fundraising with Preqin Data

Panel A: Preqin Summary Statistics

	Nobs.	Mean	Std. Dev.	5%	25%	50%	75%	95%
# Firms	160							
# Funds	271							
Fund × Quarter Level:								
IRR	9,458	0.07	0.19	-0.25	-0.01	0.09	0.16	0.32
NAV bias	9,496	-0.02	0.15	-0.26	-0.07	-0.01	0.05	0.22
Fund Level:								
Vintage Year	271	2009.38	3.09	2005	2007	2010	2012	2014
Fund Size ($MM)	271	1,067.77	1,597.93	82.50	270.85	568	1,044.55	4,200
# of Previous Funds	271	6.57	8.93	0	1	4	8	21
Final IRR	271	0.09	0.11	-0.09	0.03	0.10	0.15	0.26
Final PME	271	0.95	0.34	0.37	0.76	0.99	1.16	1.40

Panel B: IRR Boost Decomposition

	Baseline (1)	(-) Timing (2)	(-) NAV bias (3)
$\hat{\tau}$ IRR	-0.062***		
	(-3.28)		
N	9,025		
$\hat{\tau}$ IRR - {>0}		-0.010	-0.052*
		(-0.28)	(-1.82)
N		2,768	3,523

Table IA13: Panel A summarizes the funds in the Preqin sample. The sample is filtered to closed-end CRE funds with (i) vintages 2001 - 2014, (ii) at least 20 quarters of IRRs, (iii) reported IRRs during the estimated fundraising quarter, (iv) NAVs reports for at least 20% of available quarters, and (v) a non-missing fund size. Panel B reports difference-in-differences estimates of the effect of a successful fundraising on net annualized to-date IRRs using the Borusyak, Jaravel, and Spiess (2021) imputation estimator, mirroring results presented in Table IA14. Specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA14: IRR Boost Decomposition

		Difference-in-Differences Estimates After Removing the Top X% of	
	Baseline	Timing	NAV bias
	(1)	(2)	(3)
$\hat{\tau}$ IRR	-0.047***		
	(-3.63)		
N	16,968		
$\hat{\tau}$ IRR - {Top 10%}		-0.036***	-0.041***
		(-2.70)	(-3.13)
N		15,357	15,305
$\hat{\tau}$ IRR - {Top 33%}		-0.030**	-0.038***
		(-2.32)	(-2.61)
N		12,189	12,150
$\hat{\tau}$ IRR - {Top 50%}		-0.014	-0.039***
		(-0.98)	(-2.63)
N		9,902	9,569
$\hat{\tau}$ IRR - {> 0}		0.006	-0.038**
		(0.31)	(-2.52)
N		6,471	8,952
Includes: fund FE, year-quarter FE, and controls			

Table IA14: Reports difference-in-differences estimates of the effect of a successful fundraising on net annualized to-date IRRs using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. The "Baseline" column reports the estimated effect for the whole sample. The "Timing" column removes the funds with the highest X% (e.g., 10%) of gaps between IRRs and annualized to-date multiple returns as of fundraising and recalculates the treatment effect. The "NAV bias" column removes the funds with the highest X% (e.g., 10%) of average returns to NAVs not explained by cash flows or market returns over the year before the fundraising quarter and recalculates the treatment effect. The last row removes funds where measures of timing or NAV bias are positive as of the fundraising quarter. IRR Gap calculations follow Larocque, Shive, and Sustersic Stevens (2021) and NAV bias calculations follow Brown, Gredil, and Kaplan (2019). Specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA15: IRR Boost Further Decomposition

		Remove Terciles of NAV bias		
		$\hat{\tau}$ IRR - {T1 NAV bias} (1)	$\hat{\tau}$ IRR - {T2 NAV bias} (2)	$\hat{\tau}$ IRR - {T3 NAV bias} (3)
Remove Terciles of IRR Gaps	$\hat{\tau}$ IRR - {T1 Gap}	-0.044**	-0.070***	-0.055***
		(-2.12)	(-3.96)	(-2.63)
	N	8,983	7,445	6,783
	$\hat{\tau}$ IRR - {T2 Gap}	-0.040	-0.046***	-0.027
		(-1.57)	(-2.62)	(-1.44)
	N	7,615	9,209	8,941
	$\hat{\tau}$ IRR - {T3 Gap}	-0.027*	-0.028*	-0.024*
		(-1.89)	(-1.88)	(-1.72)
	N	7,285	8,655	9,787

Table IA15: Tabulates the effect of a successful fundraising on IRRs using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator after removing funds based on the tercile of the IRR timing gap $\times$ the tercile of the NAV bias as of fundraising. For example, the cell indexed by ($\hat{\tau}$ IRR - {T3 Gap}, $\hat{\tau}$ IRR - {T2 NAV bias}) reports the estimated effect of fundraising on IRRs after removing (i) all funds that have IRR gaps in the top tercile as of fundraising and (ii) all funds that have an average return not explained by market returns or cash flows over the year before fundraising in the second tercile as of fundraising. Resulting sub-samples retain unsuccessful fundraisers. IRR Gap calculations follow Larocque, Shive, and Sustersic Stevens (2021) and NAV bias calculations follow Brown, Gredil, and Kaplan (2019). All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA16: Alternate Measures of Performance

	(1) PME	(2) TVPI	(3) DPI	(4) RVPI	(5) NAV bias	(6) r_{it}^{NAV}
$\hat{\tau}$	0.026	0.066	0.174***	-0.108***	-0.005	-0.002
	(0.82)	(1.53)	(4.48)	(-3.97)	(-0.37)	(-0.17)
Year-Qtr. FE	x	x	x	x	x	x
Fund FE	x	x	x	x	x	x
$\text{PME}_{i,t-1}$	x	x	x	x	x	x
$\text{NAV}_{i,t-1}$	x	x	x	x	x	x
N	18,100	18,103	18,100	18,100	17,533	17,111

Table IA16: Tabulates the effect of a successful fundraising on several measures of performance using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA17: Fund NAVs and Cash Flows

	NAV_{it} - $NAV_{i,t-1}$		
	(1)	(2)	(3)
$Distribution_{it}$	-0.925***		-0.876***
	(-15.43)		(-18.23)
$Call_{it}$		1.033***	0.931***
		(4.74)	(4.59)
Constant	15.347***	-18.725***	0.098
	(12.99)	(-5.60)	(0.03)
Fund FE	x	x	x
Year-Qtr. FE	x	x	x
Adj R^2	0.078	0.065	0.091
N	18,103	18,103	18,103

Table IA17: Regresses the quarterly change in reported fund net asset values (NAVs) on cash flows and distributions occurring in the same quarter. 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: Determinants of Abnormal NAV Returns

	NAV bias			
	(1)	(2)	(3)	(4)
Fund Timing	-0.002	-0.002	0.003	0.003
	(-1.04)	(-1.29)	(1.56)	(1.52)
Peer-Chasing	0.020	0.060	-0.138***	-0.109***
	(0.60)	(1.45)	(-4.01)	(-2.69)
Fund Timing × Peer-Chasing		-0.050***		-0.032*
		(-2.81)		(-1.71)
Constant	-0.015***	-0.015***	-0.012***	-0.012***
	(-6.54)	(-6.64)	(-4.82)	(-4.83)
Year-Qtr. FE	x	x	x	x
Fund FE	x	x	x	x
Controls	x	x	x	x
Quarters 6 – 28			x	x
Adj R^2	0.320	0.321	0.454	0.454
N	14,988	14,988	8,757	8,757

Table IA18: Regresses abnormal quarterly changes in reported fund net asset values (NAVs) on "Fund-Timing"– the log of one plus the number of quarters spent without a follow-on fund exceeding two years and "Peer Chasing"– the difference between the IRR reported by the GPs of fund i in quarter $t-1$ and the median IRR reported by its peer funds in quarter $t-1$. This table mirrors the regressions presented in Table IV of Brown, Gredil, and Kaplan (2019). "NAV bias" denotes quarterly NAV returns not explained by cash-flows or market returns over the same quarter, following the naming convention used by Brown, Gredil, and Kaplan (2019). We winsorize NAV bias at the 1% levels, and calculate it as: $\log(NAV_{it})$ - $\log((1+r_t^b) \times NAV_{i,t-1}$ - Cash Flow$_{it})$, where r_t^b denotes the quarterly return of the U.S. Equity REITs index (excluding mortgage REITs). Peer funds include those with the same vintage and strategy. For example, one peer set may include all opportunistic funds with a 2010 vintage year. Median calculations for fund i include IRRs reported by fund i. Only fund-quarter cells where the difference between a fund's reported IRR and its peers is within 30 percentage points are considered. "Quarters 6 – 28" indicate that only quarters 6 – 28 after a fund's first capital call are included in the specification. Variable definitions follow Brown, Gredil, and Kaplan (2019). Controls include quarterly cash flows and distribution scaled by fund size. 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 IA19: Rolling NAV Volatility and Fundraising Events

	$\sigma(r_{it}^{\text{NAV}} \mid t-1:t)$			$\sigma(r_{it}^{\text{NAV}} \mid t-7:t)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$\{Fundraising Qtr. (FQ)\}	-0.046***	-0.019***	-0.013**	-0.050***	-0.034***	-0.012***
	(-4.76)	(-2.62)	(-2.52)	(-4.42)	(-4.39)	(-3.97)
$\mathbb{1}$\{FQ-8:FQ-5\}	-0.029***			-0.019**		
	(-3.15)			(-2.39)		
$\mathbb{1}$\{FQ-4:FQ-1\}	-0.031***	-0.005		-0.039***	-0.020***	
	(-3.27)	(-0.74)		(-3.70)	(-3.14)	
$\mathbb{1}$\{FQ+1:FQ+4\}	-0.035***	-0.008	-0.006	-0.051***	-0.031***	-0.011*
	(-3.33)	(-0.98)	(-0.79)	(-3.96)	(-3.19)	(-1.87)
$\mathbb{1}$\{FQ+5:FQ+8\}	-0.040***	-0.014		-0.055***	-0.036***	
	(-3.26)	(-1.48)		(-3.48)	(-2.83)	
$\mathbb{1}$\{FQ+9:FQ+12\}	-0.038***			-0.054***		
	(-2.64)			(-2.73)		
Constant	0.107***	0.081***	0.080***	0.150***	0.132***	0.119***
	(13.89)	(17.10)	(31.34)	(15.81)	(22.10)	(53.23)
Sample	[FQ±12]	[FQ±8]	[FQ±4]	[FQ±12]	[FQ±8]	[FQ±4]
Controls	x	x	x	x	x	x
Fund FE	x	x	x	x	x	x
Year-Qtr. FE	x	x	x	x	x	x
Adj R^2	0.194	0.213	0.231	0.437	0.506	0.586
N	10,202	7,580	4,659	10,477	7,798	4,793

Table IA19: Regresses rolling standard deviations of NAV returns on indicators denoting whether the volatility was calculated during the fundraising quarter (FQ). Quarterly NAV returns (r_{it}^{NAV}) are winsorized at the 1% levels and are calculated as: log(NAV_{it}) - log($NAV_{i,t-1}$ - Cash Flow$_{it}$), where i indexes the fund and t indexes the quarter. Columns 1–3 calculate volatility using a rolling two-quarter window ("$t-1:t$"). Columns 4 – 6 calculate volatility using a rolling eight-quarter window ("$t-7:t$"). Volatility calculations require two observations to be available. The unit of observation is the fund-quarter. Rows denote the position of the quarter relative to the fundraising quarter. For example, "$\mathbb{1}$\{FQ+4:FQ+8\}" is an indicator of whether an observation was measured during quarters 4 – 8 after a fundraising event took place. The "Sample" row denotes the subsample of quarters relative to the fundraising event used for the regression. For example, "[FQ±12]" indicates that the fundraising quarter and up to 12 quarters before and after the fundraising quarter for all successful fundraisers are included in the regression sample. Unsuccessful fundraisers are retained in all specifications. The omitted category in each regression is the earliest four quarters in the subsample and observations for all unsuccessful fundraisers. For example, the omitted category in regressions presented in column (1) includes fund-quarter observations 12 - 9 quarters before the fundraising event and all fund-quarter observations for unsuccessful fundraisers. Controls include quarterly calls and distributions scaled by fund size alongside the level of the quarterly NAV return. Controls are interacted with event time indicators. 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 IA20: IRRs and Lagged IRRs

	IRR_{it}				
	(1)	(2)	(3)	(4)	(5)
$IRR_{i,t-1}$	0.813***	0.962***	0.837***	0.781***	0.782***
	(71.89)	(30.51)	(25.74)	(23.38)	(23.29)
$IRR_{i,t-2}$		0.013	0.021	0.025	0.025
		(0.30)	(0.54)	(0.66)	(0.66)
$IRR_{i,t-3}$		-0.020	-0.019	-0.004	-0.005
		(-0.58)	(-0.62)	(-0.13)	(-0.15)
$IRR_{i,t-4}$		-0.022	-0.015	0.005	0.005
		(-0.99)	(-0.73)	(0.26)	(0.25)
Constant	0.007***	0.003***	0.006***	0.007***	0.007***
	(30.61)	(4.24)	(15.28)	(13.87)	(13.69)
Fund FE	x		x	x	x
Year-Qtr. FE				x	x
Fund Age (Qtrs.) FE					x
Adj R^2	0.906	0.932	0.940	0.945	0.945
N	16,559	15,204	15,204	15,204	15,196

Table IA20: Regresses the IRR reported by fund i in quarter t on several lags of reported IRRs. For example, the subscript "$i, t-2$" indicates that the IRR reported by fund i is lagged by two quarters. 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 IA21: IRR Boosts and Future Fundraising

	# Future Funds Raised					
	(1)	(2)	(3)	(4)	(5)	(6)
$-100 \times (\overline{\hat{\tau}\ \text{IRR}})_i$	0.035	0.070***	0.079**	0.057***	0.006***	0.006***
	(1.11)	(3.09)	(2.26)	(2.87)	(3.26)	(3.27)
# Prev. Funds		1.062***	1.046***		0.050***	
		(14.41)	(13.94)		(9.36)	
$100 \times$ IRR			-0.020	-0.007	0.000	0.001
			(-0.63)	(-0.28)	(0.07)	(0.46)
PME			-0.159	1.231	-0.089	0.185*
			(-0.06)	(0.96)	(-0.37)	(1.90)
log(Fund Size)			0.283	0.118	0.139*	0.051
			(0.38)	(0.20)	(1.96)	(0.82)
Constant	10.672***	5.117***	3.727	7.961**	1.253**	1.995***
	(7.94)	(8.64)	(0.68)	(2.03)	(2.23)	(4.80)
Model	OLS	OLS	OLS	OLS	Poisson	Poisson
Vintage FE	x	x	x	x	x	x
# Prev. Funds FE				x		x
Adj R^2	0.072	0.532	0.530	0.558		
Pseudo R^2					0.374	0.413
N	415	415	415	405	415	405

Table IA21: Regresses the future number of PERE funds raised by a firm (as of September 2021) on the estimated IRR boost, based on variation in fundraise timing, associated with a given fund– calculated as the average difference between observed and imputed IRRs (using the Borusyak, Jaravel, and Spiess (2021) difference-in-differences estimator) over the fund's life. This value is denoted as $-100\times(\overline{\hat{\tau}\ \text{IRR}})_i$ in the table. The -100 multiplier is included for readability. IRR and PME are measured as of fundraising quarters. Estimated treatment effects are only available for funds where the GPs successfully raised a follow-on fund. Data are observed at the fund level. Standard errors are clustered at the firm level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA22: IRR Boosting and Investor Performance Sensitivity Using "Anchor" versus "Non-Anchor" LPs

Investor Performance Sensitivity Measure	Avg. Ratio of Anchor LP Commitments to Anchor LP AUM		Avg. Ratio of Non-Anchor LP Commitments to Non-Anchor LP AUM	
	High (1)	Low (2)	High (3)	Low (4)
Determine Anchor LP(s) by the highest:				
$ Commit	-0.052***	-0.019	-0.062***	-0.003
	(-3.49)	(-0.92)	(-3.94)	(-0.14)
N	6,840	7,301	5,678	6,213
$ LP AUM	-0.055***	-0.017	-0.062***	0.002
	(-3.59)	(-0.87)	(-4.04)	(0.10)
N	6,758	7,383	5,760	6,245
LP_j Commit/LP_j AUM	-0.043***	-0.026	-0.050***	-0.011
	(-2.96)	(-1.23)	(-3.02)	(-0.48)
N	6,866	7,275	5,624	6,381
# Prev. Commits to GP	-0.055***	-0.020	-0.049***	-0.016
	(-3.38)	(-1.07)	(-2.95)	(-0.85)
N	6,995	7,146	4,530	5,077
$ Prev. Commits to GP	-0.054***	-0.017	-0.055***	-0.019
	(-3.54)	(-0.84)	(-3.26)	(-1.04)
N	7,072	7,069	4,546	5,038
# Future Commits to GP	-0.055***	-0.017	-0.054***	-0.005
	(-3.58)	(-0.85)	(-3.59)	(-0.21)
N	7,075	7,066	5,297	5,780
$ Future Commits to GP	-0.047***	-0.021	-0.066***	-0.027
	(-2.97)	(-1.04)	(-4.14)	(-1.39)
N	6,786	7,355	5,302	5,858

Table IA22: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by measures of investors' sensitivities to fund returns using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Investor performance sensitivity for each fund is calculated using only either the commitment made by the fund's "anchor" LP(s) (columns 1 and 2) or the remaining "non-anchor" LPs (columns 3 and 4). Rows indicate the variable used to estimate a fund's anchor LP(s). We average individual LP sensitivities together if funds have multiple anchor LPs, i.e. if there is a tie among LPs for the highest anchor characteristic. "High" indicates the sensitivity measure is above the sample median. "Low" indicates the sensitivity measure is below the sample median. The resulting sub-samples retain all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA23: IRR Boost Types and Public Pension LP Catering Incentives

	PERE Fund-level Avg. Ratio of Public Pension Commitments to Public Pension AUM					
	High			Low		
	Baseline (1)	Timing (2)	NAV bias (3)	Baseline (4)	Timing (5)	NAV bias (6)
$\hat{\tau}$ IRR	-0.044***			-0.022		
	(-2.65)			(-1.15)		
N	5,420			6,026		
$\hat{\tau}$ IRR - {Top 10%}		-0.046***	-0.049***		-0.009	-0.017
		(-2.77)	(-3.01)		(-0.53)	(-0.98)
N		5,120	5,172		5,476	5,543
$\hat{\tau}$ IRR - {Top 33%}		-0.023	-0.048***		0.007	-0.011
		(-1.23)	(-2.60)		(0.37)	(-0.59)
N		3,995	4,105		4,565	4,572
$\hat{\tau}$ IRR - {Top 50%}		-0.004	-0.038*		0.010	-0.015
		(-0.20)	(-1.75)		(0.47)	(-0.77)
N		3,424	3,184		3,959	3,997
$\hat{\tau}$ IRR - { > 0 }		0.022	-0.045*		0.041	-0.009
		(0.80)	(-1.91)		(1.64)	(-0.46)
N		2,615	2,987		2,775	3,753

Includes: fund FE, year-quarter FE, and controls

Table IA23: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by the average weight of each fund in its' *U.S. defined benefit public pension investors' portfolios* using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. The "Baseline" column reports the estimated effect for the whole sample. The "Timing" column removes the funds with the highest X% (e.g., 10%) of gaps between IRRs and annualized to-date multiple returns as of fundraising and recalculates the treatment effect. The "NAV bias" column removes the funds with the highest X% (e.g., 10%) of average returns to NAVs not explained by cash flows or market returns over the year before the fundraising quarter and recalculates the treatment effect. The last row removes funds where measures of timing or NAV bias are positive as of the fundraising quarter. "High" indicates the sensitivity measure is above the sample median (0.2%). "Low" indicates the sensitivity measure is below the sample median. The resulting sub-samples retain all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA24: IRR Boost Types LP Catering Incentives Excluding U.S. Public Pension LPs

	PERE Fund-level Avg. Ratio of LP Commitments to LP AUM (Excluding U.S. Public Pension LPs)					
	High			Low		
	Baseline (1)	Timing (2)	NAV bias (3)	Baseline (4)	Timing (5)	NAV bias (6)
$\hat{\tau}$ IRR	-0.044***			-0.036		
	(-2.98)			(-1.60)		
	4,756			4,380		
$\hat{\tau}$ IRR - {Top 10%}		-0.042***	-0.046***		-0.007	-0.017
		(-2.72)	(-3.01)		(-0.30)	(-0.76)
N		5,623	5,527		5,248	5,282
$\hat{\tau}$ IRR - {Top 33%}		-0.024	-0.048***		-0.021	-0.018
		(-1.36)	(-2.86)		(-1.17)	(-0.80)
N		4,731	4,729		4,510	4,472
$\hat{\tau}$ IRR - {Top 50%}		-0.004	-0.041*		-0.013	-0.041**
		(-0.19)	(-1.88)		(-0.67)	(-2.12)
N		4,150	3,721		3,794	3,768
$\hat{\tau}$ IRR - { > 0 }		0.027	-0.042*		-0.001	-0.034*
		(1.05)	(-1.88)		(-0.04)	(-1.80)
N		3,029	3,579		2,918	3,548

Includes: fund FE, year-quarter FE, and controls

Table IA24: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by the average weight of each fund in its' investors' portfolios *(excluding U.S. public pension fund LPs)* using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. The "Baseline" column reports the estimated effect for the whole sample. The "Timing" column removes the funds with the highest X% (e.g., 10%) of gaps between IRRs and annualized to-date multiple returns as of fundraising and recalculates the treatment effect. The "NAV bias" column removes the funds with the highest X% (e.g., 10%) of average returns to NAVs not explained by cash flows or market returns over the year before the fundraising quarter and recalculates the treatment effect. The last row removes funds where measures of timing or NAV bias are positive as of the fundraising quarter. "High" indicates the sensitivity measure is above the sample median (0.2%). "Low" indicates the sensitivity measure is below the sample median. The resulting sub-samples retain all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA25: Alternate Investor Performance Sensitivity Measurements

Investor Performance Sensitivity Measure	Avg. Ratio of LP Commitments to LP AUM		Avg. Ratio of LP Commitments to LP AUM in Alt. Assets		Avg. Ratio of LP Commitments to Target LP AUM in RE Assets		Avg. Ratio of LP Commitments to LP 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	-0.067***	-0.005	-0.071***	0.008	-0.058***	0.001
	(-4.22)	(-0.03)	(-4.05)	(-0.24)	(-4.55)	(0.35)	(-3.38)	(0.03)
N	7,094	7,047	7,018	7,043	6,711	6,898	6,813	6,723
Value-Weighted	-0.063***	-0.015	-0.049***	-0.034*	-0.101***	-0.016	-0.058***	-0.030
	(-4.07)	(-0.78)	(-2.69)	(-1.90)	(-5.57)	(-0.53)	(-4.89)	(-1.08)
N	6,485	6,845	2,178	2,145	1,378	1,323	1,310	1,327
Panel AUM	-0.041**	-0.029	-0.046***	-0.028*	-0.040**	-0.032*	-0.047***	-0.025
	(-2.45)	(-1.64)	(-2.60)	(-1.65)	(-2.26)	(-1.91)	(-2.86)	(-1.39)
N	5,708	6,120	5,054	5,410	5,601	6,052	4,947	5,577
No Imputed LPs	-0.065***	-0.012	-0.058***	-0.025	-0.063***	-0.003	-0.052***	0.000
	(-4.22)	(-0.66)	(-3.74)	(-1.47)	(-4.11)	(-0.12)	(-3.14)	(0.00)
N	7,016	7,125	7,002	7,059	6,800	6,809	6,757	6,812
No Imputed Commits	-0.052***	-0.016	-0.032	-0.037**	-0.052***	0.004	-0.052***	0.005
	(-3.48)	(-0.79)	(-1.63)	(-2.04)	(-3.52)	(0.18)	(-3.59)	(0.20)
N	6,773	7,368	6,614	6,826	5,675	6,474	5,523	5,742

Includes: fund FE, year-quarter FE, and controls

Table IA25: Reports difference-in-differences estimates of the effect of a successful fundraising on reported net IRRs after splitting the sample by different 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 fund-level investor performance sensitivity equals the median weight of the fund in its' investors' portfolios. "Value-Weighted" indicates that fund-level investor performance sensitivity equals the average weight of the fund in its' investors' portfolios, weighted by the size of the commitments. "Panel AUM" indicates that fund-level investor performance sensitivity equals the average weight of the fund in its' investors' portfolios, where the size of investor portfolios change dynamically, equalling the value of actuarial assets (reported in the Public Plans Database) for public pension funds that are LPs of the PERE fund as of the commitment year. The remaining rows calculate investor performance sensitivity without imputing the value of commitments. "High" indicates the sensitivity measure is above the sample median. "Low" indicates the sensitivity measure is below the sample median. Resulting sub-samples retain unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA26: Additional Alternate Investor Performance Sensitivity Measurements

	Rolling 3 Commitments		Rolling 5 Commitments		Rolling 10 Commitments	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\tau}$ IRR (Only PERE)	-0.051***	-0.014	-0.051***	-0.012	-0.056***	-0.006
	(-3.10)	(-0.70)	(-3.20)	(-0.56)	(-3.48)	(-0.26)
N	7,271	6,833	7,298	6,741	7,156	6,752
$\hat{\tau}$ IRR (Only PERE; No-imputation)	-0.047***	-0.018	-0.024	-0.033*	-0.049***	-0.025
	(-2.65)	(-0.93)	(-1.03)	(-1.95)	(-2.99)	(-1.41)
N	6,868	7,057	6,986	6,744	6,831	6,408
$\hat{\tau}$ IRR (All PE)	-0.055***	-0.007	-0.050***	-0.008	-0.025	-0.018
	(-3.33)	(-0.32)	(-2.87)	(-0.38)	(-0.97)	(-1.01)
N	7,362	6,625	6,999	6,534	6,284	6,001
$\hat{\tau}$ IRR (All PE; No-imputation)	-0.048***	-0.010	-0.044**	-0.010	-0.024	-0.015
	(-2.77)	(-0.47)	(-2.40)	(-0.44)	(-0.87)	(-0.88)
N	6,765	6,779	6,589	6,202	5,716	5,659
Includes: fund FE, year-quarter FE, and controls						

Table IA26: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by measures of investors' sensitivities to fund returns using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Investor performance sensitivity at the fund level (i) is calculated as:

$$\text{Investor Performance Sensitivity}_i = \frac{1}{J} \sum_{j \le J} \frac{c_{ij}}{\bar{c}_j},$$

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 of commitments LP j made to other PE funds. The column headers denote the previous number of commitments used in the rolling average. For example, "Rolling 5 Commitments" indicates that the commitment LP j made to fund i (c_{ij}) and the previous four commitments that LP j made to other PERE funds are used in the calculation. "Only PERE" indicates that only commitments to PERE are used. "All PE" indicates that adjacent LP commitments to all PE funds in our commitments data (i.e., buyout, venture, real estate, infrastructure, private debt, and natural resources funds) are used. "No-imputation" indicates that c_{ij} are not imputed for the calculation (Section IA.2 discusses commitment imputations). "High" indicates the sensitivity measure is above the sample median. "Low" indicates the sensitivity measure is below the sample median. The resulting sub-samples retain all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA27: IRR Boosts by Catering Incentive Quintiles

Investor Performance Sensitivity Quintile:	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q5
$\hat{\tau}$ IRR	-0.008	-0.034**	-0.045*	-0.050***	-0.060***
	(-0.35)	(-2.06)	(-1.92)	(-2.72)	(-3.19)
Year-Qtr. FE	x	x	x	x	x
Fund FE	x	x	x	x	x
$PME_{i,t-1}$	x	x	x	x	x
$NAV_{i,t-1}$	x	x	x	x	x
N	3,578	3,587	3,600	3,493	3,516

Table IA27: Reports difference-in-differences estimates of the effect of a successful fundraising on reported net IRRs after splitting the sample by measures of investor sensitivity to fund returns using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Investor performance sensitivity is calculated according to equation (2). "Q1" indicates the fund is assigned a sensitivity measure in the first quintile. "Q5" indicates the fund is assigned a sensitivity measure in the fifth quintile. Resulting sub-samples retain unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA28: IRR Boost Types and Catering Incentives

	Fund-level Avg. Ratio of LP Commitments to LP AUM					
	High			Low		
	Baseline (1)	Timing (2)	NAV bias (3)	Baseline (4)	Timing (5)	NAV bias (6)
$\hat{\tau}$ IRR	-0.064***			-0.011		
	(-4.36)			(-0.59)		
	6,937			7,204		
$\hat{\tau}$ IRR - {Top 10%}		-0.055***	-0.058***		-0.009	-0.008
		(-3.73)	(-3.98)		(-0.49)	(-0.42)
N		6,231	6,379		6,818	6,616
$\hat{\tau}$ IRR - {Top 33%}		-0.042**	-0.058***		-0.008	-0.006
		(-2.45)	(-3.53)		(-0.48)	(-0.31)
N		4,916	5,062		5,826	5,604
$\hat{\tau}$ IRR - {Top 50%}		-0.028	-0.053***		-0.000	-0.021
		(-1.40)	(-2.82)		(-0.02)	(-1.21)
N		4,146	3,909		5,050	4,735
$\hat{\tau}$ IRR - {> 0}		-0.006	-0.045**		0.019	-0.024
		(-0.23)	(-2.37)		(0.92)	(-1.29)
N		2,906	3,714		3,680	4,489
Includes: fund FE, year-quarter FE, and controls						

Table IA28: Reports difference-in-differences estimates of the effect of a successful fundraising on reported IRRs after splitting the sample by the average weight of each fund in its' investors' portfolios using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. The "Baseline" column reports the estimated effect for the whole sample. The "Timing" column removes the funds with the highest X% (e.g., 10%) of gaps between IRRs and annualized to-date multiple returns as of fundraising and recalculates the treatment effect. The "NAV bias" column removes the funds with the highest X% (e.g., 10%) of average returns to NAVs not explained by cash flows or market returns over the year before the fundraising quarter and recalculates the treatment effect. The last row removes funds where measures of timing or NAV bias are positive as of the fundraising quarter. "High" indicates the sensitivity measure is above the sample median. "Low" indicates the sensitivity measure is below the sample median. The resulting sub-samples retain all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA29: IRRs, Lagged IRRs, and Catering Incentives

	IRR_{it}	
Catering Incentives:	High (1)	Low (2)
$IRR_{i,t-1}$	0.782***	0.777***
	(13.23)	(15.59)
$IRR_{i,t-2}$	0.011	0.036
	(0.20)	(0.83)
$IRR_{i,t-3}$	-0.023	0.015
	(-0.58)	(0.37)
$IRR_{i,t-4}$	0.019	-0.017
	(0.87)	(-0.39)
Constant	0.011***	0.000*
	(9.60)	(1.89)
Fund FE	x	x
Year-Qtr. FE	x	x
Age FE	x	x
Adj R^2	0.945	0.946
N	5,439	5,681

Table IA29: Regresses the IRR reported by fund i in quarter t on several lags of reported IRRs separately among subsets of funds that face high and low catering incentives (equation (2)). For example, the subscript "$i, t-2$" indicates that the IRR reported by fund i is lagged by two quarters. "High" indicates that the fund's investor performance sensitivity is above the sample median. "Low" indicates that the fund's investor performance sensitivity measure is below the sample median. The regression specifications in this table reflect only the most stringent specification reported in Table IA20. 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 IA30: S&P 500 Benchmark

	NAV Return$_{it}$			
	(1)	(2)	(3)	(4)
r_t^b	0.214***	0.206***	0.219***	0.230***
	(8.68)	(8.48)	(8.93)	(9.40)
r_{t-1}^b		0.124***	0.116***	0.136***
		(5.42)	(5.17)	(6.09)
r_{t-2}^b			0.110***	0.098***
			(4.77)	(4.30)
r_{t-3}^b				0.191***
				(8.50)
Investor Performance Sensitivity$_i$ $\times r_t^b$	-0.179**	-0.161**	-0.164**	-0.147**
	(-2.53)	(-2.25)	(-2.57)	(-2.37)
Investor Performance Sensitivity$_i$ $\times r_{t-1}^b$		-0.141**	-0.139*	-0.107
		(-1.98)	(-1.87)	(-1.49)
Investor Performance Sensitivity$_i$ $\times r_{t-2}^b$			-0.036	-0.086
			(-0.24)	(-0.53)
Investor Performance Sensitivity$_i$ $\times r_{t-3}^b$				0.309**
				(1.97)
Investor Performance Sensitivity$_i$	0.015	0.017	0.018	0.013
	(0.97)	(1.13)	(1.10)	(0.79)
Constant	-0.125***	-0.125***	-0.125***	-0.125***
	(-3.18)	(-3.19)	(-3.19)	(-3.19)
Controls	x	x	x	x
Vintage FE	x	x	x	x
Adj R^2	0.055	0.057	0.059	0.065
N	12,465	12,465	12,465	12,465

Table IA30: Regresses the quarterly returns on fund NAVs on investor performance sensitivity and quarterly benchmark returns (r^b). The unit of observation is the fund-quarter. Regression samples include all funds where known commitments represent at least 5% of total fund commitments in Preqin. Quarterly NAV returns are winsorized at the 1% levels and are calculated as: log(NAV_{it}) - log($NAV_{i,t-1}$ - Cash Flow$_{it}$), where i indexes the fund and t indexes the quarter. Investor performance sensitivity is the average weight of the fund in its' investors' portfolios, fixed at the fund level. The benchmark return is the value-weighted S&P 500 return. Controls include the size of the fund, whether the GPs of the fund raised a follow-on fund, quarterly capital calls, quarterly distributions, and the cumulative percent of committed capital called as of a given quarter. 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 IA31: Market Return Pass-Through by Year

	Model (1): Baseline				Model (2): Fund FE and Controls			
Year	$\hat{\beta}^{\text{Mkt.}}$	t-stat.	Adj R^2	N	$\hat{\beta}^{\text{Mkt.}}$	t-stat.	Adj R^2	N
2006	0.029	(0.10)	-0.003	347	0.217	(0.42)	0.201	339
2007	-0.292**	(-3.22)	0.008	639	-0.325**	(-3.72)	0.050	620
2008	0.442**	(4.56)	0.133	914	0.445**	(4.01)	0.129	906
2009	0.009	(0.31)	-0.001	1,078	0.012	(0.33)	0.129	1,074
2010	0.129	(0.89)	0.001	1,183	0.106	(0.62)	0.123	1,177
2011	0.101	(1.88)	0.004	1,336	0.092*	(2.42)	0.173	1,323
2012	0.029	(0.34)	-0.001	1,489	0.012	(0.16)	0.303	1,478
2013	-0.040	(-0.96)	-0.000	1,615	-0.017	(-0.47)	0.278	1,607
2014	0.130*	(3.09)	0.002	1,663	0.128	(2.31)	0.228	1,662
2015	-0.034	(-0.35)	-0.001	1,618	-0.082	(-1.34)	0.308	1,613
2016	0.166*	(2.59)	0.001	1,458	0.325**	(5.61)	0.323	1,451
2017	-0.369*	(-2.44)	-0.001	1,478	-0.358	(-1.94)	0.475	1,473
2018	-0.068	(-0.65)	-0.000	1,339	-0.108	(-0.82)	0.538	1,329
2019	-0.099*	(-3.76)	-0.000	954	-0.095**	(-4.38)	0.604	946

Table IA31: Tabulates the regression coefficient $\hat{\beta}^{\text{Mkt.}}$ from year-by-year regressions of fund-quarter NAV returns on quarterly benchmark returns. The benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. Model (2) additionally includes a fund fixed effect and cash flow controls (quarterly calls and distributions scaled by fund size). Funds stop entering the panel in 2014. Standard errors are clustered at the year-quarter level, effectively calculating test statistics as if there are four observations each year. Test statistics ("t-stat.") are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA32: List of Pension Fund Board Changes During our Sample Period

State	Pension Fund	Year	% State-Political (after change)	Change (p.p.)	Change (%)	# Active PERE Fund Investments During Change
AK	Alaska Retirement Management Board	2006	33.3%	20.8%	166.7%	4
AZ	Arizona Public Safety Personnel Retirement System	2011	42.9%	22.9%	114.3%	15
AZ	Arizona Public Safety Personnel Retirement System	2017	44.4%	1.6%	3.7%	20
CA	San Diego City ERS	2005	7.7%	-15.4%	-66.7%	1
CA	San Jose Federated City ERS	2011	0.0%	-42.9%	-100.0%	4
CA	San Jose Police and Fire Department Retirement Plan	2011	0.0%	-57.1%	-100.0%	5
CO	Colorado Public Employees' Retirement Association	2007	6.7%	-5.8%	-46.7%	13
IL	State Universities Retirement System of Illinois	2010	9.1%	9.1%		3
IL	Teachers' Retirement System of the State of Illinois	2009	7.7%	-1.4%	-15.4%	10
IN	Indiana PERF (until 2009)	2006	16.7%	16.7%		2
IN	Indiana Public Retirement System	2012	33.3%	16.7%	100.0%	4
KS	Kansas Public ERS	2013	22.2%	11.1%	100.0%	17
KY	Kentucky Retirement Systems	2014	30.8%	19.7%	176.9%	4
KY	Kentucky Retirement Systems	2017	23.5%	-7.2%	-23.5%	4
KY	Kentucky Teachers' Retirement System	2017	18.2%	-4.0%	-18.2%	4
LA	Louisiana Municipal Police ERS	2011	40.0%	21.8%	120.0%	2
LA	Louisiana School ERS	2008	36.4%	-3.6%	-9.1%	1
LA	Louisiana School ERS	2013	41.7%	5.3%	14.6%	3
LA	Teachers' Retirement System of Louisiana	2013	29.4%	4.4%	17.6%	17
MD	Baltimore City ERS	2017	22.2%	7.9%	55.6%	1
MD	Baltimore Fire & Police ERS	2010	36.4%	3.0%	9.1%	4
MD	ERS of Baltimore County	2016	45.5%	-17.0%	-27.3%	1
MD	Maryland State Retirement and Pension System	2013	33.3%	4.8%	16.7%	23
MI	City of Detroit General Retirement System	2016	0.0%	-30.0%	-100.0%	4
MI	Michigan Department of Treasury	2019	40.0%	-60.0%	-60.0%	11
MO	Missouri Department of Transportation & Patrol ERS	2008	63.6%	-6.4%	-9.1%	6
NE	Nebraska Investment Council	2017	0.0%	-40.0%	-100.0%	1
NH	New Hampshire Retirement System	2007	28.6%	5.5%	23.8%	2
NH	New Hampshire Retirement System	2011	38.5%	9.9%	34.6%	9
OH	Ohio Police & Fire Pension Fund	2004	0.0%	-33.3%	-100.0%	4
OH	Ohio PERS	2004	9.1%	-24.2%	-72.7%	4
OH	Ohio State Highway Patrol Retirement System	2004	9.1%	-19.5%	-68.2%	1
OH	School ERS of Ohio	2005	0.0%	-28.6%	-100.0%	4
OH	State Teachers' Retirement System of Ohio	2005	9.1%	-24.2%	-72.7%	7
PA	Pennsylvania Public School ERS	2018	53.3%	6.7%	14.3%	29
PA	Pennsylvania State ERS	2018	54.5%	9.1%	20.0%	22
RI	ERS of Rhode Island	2007	33.3%	-22.2%	-40.0%	9
SC	South Carolina Retirement Systems	2013	16.7%	-3.3%	-16.7%	8
SC	South Carolina Retirement Systems	2018	0.0%	-16.7%	-100.0%	8
TX	Dallas Police & Fire Pension System	2018	0.0%	-33.3%	-100.0%	2
TX	Fort Worth Employees' Retirement Fund	2008	7.7%	7.7%		4
TX	Houston Municipal Employees' Pension System	2006	9.1%	-13.1%	-59.1%	4
TX	Houston Municipal Employees' Pension System	2014	0.0%	-9.1%	-100.0%	11
VT	Vermont Pension Investment Committee	2008	16.7%	-18.6%	-52.8%	1

Table IA32: Lists the 44 pension fund board composition changes occurring during our sample period, where pension fund j's % State-Political$_{jt}$ measured in year t differs from the same pension fund's % State-Political$_{j,t-1}$ measurement in the previous year. "% State-political" is the percentage of board members who are politically appointed (state-appointed and state-ex officio), tabulated to reflect board compositions after changes occur. We tabulate board composition changes in percentage points ("p.p.") and percentage changes ("%"). For example, our data indicate that from 2017 to 2018, the percent of Pennsylvania State ERS board trustees that are state-political or state-appointed increased from 45.4% to 54.5%, reflecting a 9.1 percentage point increase, or a 20 percent change. "# Active PERE Fund Investments During Change" tabulates the number of active PERE funds in our sample for which the pension fund was an LP during its board composition change. Andonov, Hochberg, and Rauh (2018) make pension board composition data available, and list all pension board changes in their sample in their internet appendix.

Table IA33: Determinants of Pension Fund Board Changes

	$\mathbb{1}$(Board Change)						$\mathbb{1}$(Increase in % State-Political)	$\mathbb{1}$(Decrease in % State-political)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-yr. Pension Fund Return	0.043	0.011	0.055	-0.046	-0.007	-0.014	0.044	-0.051
	(0.89)	(0.16)	(0.80)	(-0.47)	(-0.11)	(-0.22)	(1.15)	(-0.92)
5-yr. Pension Fund Return	-0.065	-0.180	-0.409	-0.227	-0.113	-0.099	-0.182	0.069
	(-0.57)	(-0.70)	(-1.41)	(-0.74)	(-0.44)	(-0.36)	(-1.09)	(0.35)
10-yr. Pension Fund Return	-0.248	-0.589	-0.549	-0.383	-0.379	-0.630	-0.276	-0.102
	(-0.97)	(-1.25)	(-1.03)	(-0.72)	(-0.81)	(-1.29)	(-0.75)	(-0.36)
W-avg. PERE Fund r_{it}^{NAV}			0.012					
			(0.46)					
W-avg. PERE Fund $r_{i,t-1}^{NAV}$			-0.023					
			(-0.58)					
1-yr. Peer Pension Fund Return$_{jt}$				0.054				
				(0.41)				
1-yr. Peer Pension Fund Return$_{j,t-1}$				-0.130				
				(-1.30)				
Reported Funding Ratio					-0.307***	-0.103***	-0.091*	-0.216**
					(-3.07)	(-3.26)	(-1.95)	(-2.45)
log(Pension Fund Assets)					0.066	-0.003	0.003	0.063
					(1.01)	(-1.00)	(0.21)	(1.02)
Alternatives % Target					-0.092	0.075	0.028	-0.120
					(-0.98)	(1.64)	(0.60)	(-1.41)
% State-political$_{j,t-1}$						-0.004		
						(-0.33)		
# Board Members$_{j,t-1}$						0.000		
						(0.01)		
Constant	0.039**	0.071**	0.081**	0.072**	-0.777	0.179***	0.050	-0.827
	(2.26)	(2.36)	(2.51)	(2.17)	(-0.76)	(3.08)	(0.21)	(-0.85)
Year FE		x	x	x	x	x	x	x
Pension Fund FE		x	x	x	x		x	x
Adj R^2	-0.001	-0.004	0.017	-0.010	0.005	0.019	-0.005	0.018
N	1,331	1,329	1,046	973	1,269	1,219	1,269	1,269

Table IA33: Regresses indicators for whether pension fund j's board composition changed in year t. The unit of observation is the public pension fund-year. The sample period is from 2002 to 2019. Regression samples only include public pension LPs from Preqin that invested in a PERE fund in our sample of funds from Cambridge Associates (CA). Table IA32 lists pension board changes. "W-avg. PERE r_{it}^{NAV}" equals the commitment weighted average NAV return of LP j's active PERE fund investments in year t that are in our CA data. Peer pension funds are other pension funds in the same state. "Alternatives % Target" equals the target allocation to private equity, real estate, hedge funds, miscellaneous alternatives, and other asset classes. Pension characteristics are from the public plans database. Andonov, Hochberg, and Rauh (2018) make board composition data available. 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 IA34: Placebo Test for NAV Return Boosting and Public Pension LP Board Politicization

	NAV Return$_{it}$			NAV bias		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. % Other-trustees$_{it}$	0.670	-0.117	0.359	0.529	-0.701	-0.297
	(0.96)	(-0.09)	(0.27)	(1.01)	(-0.68)	(-0.28)
Fund Timing		0.014	0.009		0.045	0.031
		(0.14)	(0.10)		(0.51)	(0.35)
Peer-Chasing		-0.125	-0.103		-0.213	-0.186
		(-0.70)	(-0.57)		(-1.14)	(-0.98)
Constant	0.003	-0.132	-0.263	-0.096***	-0.005	-0.157
	(0.15)	(-0.20)	(-0.39)	(-6.66)	(-0.01)	(-0.24)
Fund FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
Fund Year FE			x			x
Post-Fundraise FE			x			x
Controls		x	x		x	x
Adj R^2	0.293	0.313	0.318	0.330	0.371	0.375
N	2,415	1,954	1,953	2,443	1,980	1,979

Table IA34: Regresses annual NAV returns and annual NAV bias on the average fraction of a fund's public pension LP trustees that are public-elected, public-appointed, participant-ex-officio, or state-elected ("% Other") as of a given year, calculated as:

$$\text{Avg. \% Other-trustees}_{it} = \frac{\sum_j c_{ij} \times \text{\% Other-trustees}_{jt}}{\sum_j c_{ij}},$$

where i indexes the PERE fund, t indexes the year of the observation, j denotes public pension LP j of fund i, c_{ij} indicates the dollar value of the capital commitment LP j made to fund i (which weights pension fund other trustee percentages). These trustees are grouped as "other" by Andonov, Hochberg, and Rauh (2018). The unit of observation is the PERE fund-year. Table IA32 lists pension board composition changes in our sample. Controls include annual distributions and capital calls scaled by fund size, "Fund-Timing"– the log of one plus the number of years spent without a follow-on fund exceeding two years, and "Peer Chasing"– the difference between the end-of-year IRR reported by the GPs of fund i in year $t-1$ and the median IRR reported by its peer funds in year $t-1$. Fund-timing and peer-chasing follow Brown, Gredil, and Kaplan (2019) and are further described in Table IA18. We also include the commitment-weighted pension average: reported funding ratios, number of board trustees, and number of LPs with board composition data available in a given PERE fund-year cell as controls. The "Fund Year" fixed effect calculates the age of the fund in years. The "Post-Fundraise" fixed effect equals one if the fund year is after the fundraising quarter and zero otherwise. Similar results attain in other placebo tests so long as state-political trustees are excluded. 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 IA35: Placebo Test for NAV Return Smoothing and Public Pension LP Board Politicization

	NAV Return$_{it}$			
	(1)	(2)	(3)	(4)
r_t^{RE}	-0.058	-0.058		
	(-0.55)	(-0.55)		
r_{t-1}^{RE}	0.375***	0.375***		
	(4.66)	(4.66)		
$r_t^{S\&P}$			0.161	0.161
			(1.11)	(1.11)
$r_{t-1}^{S\&P}$			0.427**	0.428**
			(2.35)	(2.35)
Avg. % Other-trustee$_{it}$ $\times$ r_t^{RE}	0.564	0.568		
	(1.22)	(1.21)		
Avg. % Other-trustee$_{it}$ $\times$ r_{t-1}^{RE}	0.309	0.308		
	(0.97)	(0.97)		
Avg. % Other-trustee$_{it}$ $\times$ $r_t^{S\&P}$			-0.680	-0.679
			(-0.69)	(-0.69)
Avg. % Other-trustee$_{it}$ $\times$ $r_{t-1}^{S\&P}$			0.118	0.111
			(0.14)	(0.13)
Avg. % Other-trustee$_{it}$	0.319	0.316	0.587	0.589
	(0.29)	(0.29)	(0.49)	(0.49)
Constant	-0.293	-0.296	-0.475	-0.478
	(-0.88)	(-0.89)	(-1.23)	(-1.25)
Fund FE	x	x	x	x
Fund Year FE	x	x	x	x
Post-Fundraise FE		x		x
Controls	x	x	x	x
Adj R^2	0.297	0.296	0.282	0.282
N	1,953	1,953	1,953	1,953

Table IA35: Regresses annual NAV returns on lagged and contemporaneous market returns interacted with the average fraction of a fund's public pension trustees that are public-elected, public-appointed, plan-ex-officio, or state-elected ("% Other") as of a given year. We calculate this fraction as: Avg. % Other-trustees$_{it}$ = $(\sum_j c_{ij} \times \%\text{ Other-trustees}_{jt})/(\sum_j c_{ij})$, where i indexes the PERE fund, t indexes the year of the observation, j denotes public pension LP j of fund i, c_{ij} indicates the dollar value of the capital commitment LP j made to fund i (which weights pension fund other trustee percentages). These trustees are grouped as "other" by Andonov, Hochberg, and Rauh (2018). The unit of observation is the PERE fund-year. Table IA32 lists pension board composition changes in our sample. For year t, r_t^{RE} denotes the return of the FTSE Nareit U.S. Equity REITs index (which excludes mortgage REITs), and $r_t^{S\&P}$ denotes the value-weighted S&P 500 return. Controls include annual distributions and capital calls scaled by fund size, "Fund-Timing"– the log of one plus the number of years spent without a follow-on fund exceeding two years, and "Peer Chasing"– the difference between the end-of-year IRR reported by the GPs of fund i in year $t-1$ and the median IRR reported by its peer funds in year $t-1$. Fund-timing and peer-chasing follow Brown, Gredil, and Kaplan (2019) and are further described in Table IA18. We also include the commitment-weighted pension average: reported funding ratios, number of board trustees, and number of LPs with board composition data available in a given PERE fund-year cell as controls. The "Fund Year" fixed effect calculates the age of the fund in years. The "Post-Fundraise" fixed effect equals one if the fund year is after the fundraising quarter and zero otherwise. Similar results attain in other placebo tests so long as state-political trustees are excluded. Standard errors are clustered at the year level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA36: IRR Boosting, Investor Characteristics, and Fund Characteristics

Panel A: Investor Characteristics

	LP 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	-0.034*	-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	-0.038**	-0.049***	-0.025	-0.046***	-0.053***	-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 IA36: 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. Panel B partitions the sample using fund characteristics. Characteristics are defined in Section 3.5. The resulting sub-samples retain all unsuccessful fundraisers. 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 the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA37: Catering Incentives, IRR Boosting, and Additional Cross-Sectional Variation

	$\frac{\sum \text{Commits}}{\text{Fund Size}}$		Public Pension % LPs		Fund Size		# Active Funds		Avg. LP AUM	
	High	Low	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Above-Median Investor Performance Sensitivity										
$\hat{\tau}$ IRR	-0.051**	-0.077***	-0.055**	-0.061***	-0.047**	-0.088***	-0.051***	-0.084***	-0.039*	-0.079***
	(-3.18)	(-3.94)	(-2.94)	(-3.57)	(-2.90)	(-4.86)	(-3.29)	(-4.28)	(-2.08)	(-4.92)
N	5,342	2,806	3,649	4,499	5,281	2,867	5,545	2,603	3,794	4,354
Below-Median Investor Performance Sensitivity										
$\hat{\tau}$ IRR	0.012	-0.035	-0.008	-0.022	-0.011	-0.026	-0.018	-0.012	-0.002	-0.008
	(0.49)	(-1.54)	(-0.46)	(-0.89)	(-0.46)	(-1.42)	(-0.89)	(-0.54)	(-0.08)	(-0.33)
N	5,247	3,168	4,637	3,778	4,181	4,234	4,942	3,473	4,798	3,617
Includes: fund FE, year-quarter FE, and controls										

Table IA37: 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 other fund and investor characteristics using the Borusyak, Jaravel, and Spiess (2021) imputation estimator. Investor performance sensitivity is calculated according to equation (2). Columns labeled "High" indicate that the value assigned to the fund is above the sample median. Columns labeled "Low" indicate that the value assigned to the fund is below the sample median. ($\sum$ Commits)/Fund Size equals the sum of available commitments as a percentage of the fund size. "# Active Funds" calculates the number of other ongoing funds sponsored by the GP of the fund. These data are retrieved from Preqin. Funds are assumed to be ongoing if they are within their first ten years as of the first capital call date for the current fund. The resulting sub-samples keep all unsuccessful fundraisers. The unit of observation is the fund-quarter. All specifications include fund and year-quarter fixed effects, and one quarter lags of 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 IA38: Catering Incentives and Return Smoothing with Additional Controls

	NAV Return$_{it}$			
	(1)	(2)	(3)	(4)
r^b_t	0.110***	0.104***	0.120***	0.127***
	(6.40)	(6.12)	(6.72)	(7.09)
r^b_{t-1}		0.040**	0.030*	0.062***
		(2.29)	(1.77)	(3.42)
r^b_{t-2}			0.053***	0.034*
			(2.76)	(1.77)
r^b_{t-3}				0.107***
				(6.02)
Investor Performance Sensitivity$_i$ $\times r^b_t$	-0.143**	-0.123**	-0.122***	-0.106**
	(-2.55)	(-2.17)	(-2.78)	(-2.43)
Investor Performance Sensitivity$_i$ $\times r^b_{t-1}$		-0.123**	-0.123**	-0.060
		(-2.20)	(-2.14)	(-1.26)
Investor Performance Sensitivity$_i$ $\times r^b_{t-2}$			-0.002	-0.046
			(-0.02)	(-0.52)
Investor Performance Sensitivity$_i$ $\times r^b_{t-3}$				0.229***
				(3.13)
Investor Performance Sensitivity$_i$	0.017	0.020	0.020	0.013
	(1.04)	(1.17)	(1.16)	(0.79)
Constant	-0.124***	-0.125***	-0.126***	-0.128***
	(-3.20)	(-3.23)	(-3.24)	(-3.29)
Baseline, Fund, and Investor Controls	x	x	x	x
Vintage FE	x	x	x	x
Adj R^2	0.053	0.054	0.054	0.058
N	12,465	12,465	12,465	12,465

Table IA38: Regresses the quarterly NAV returns on investor performance sensitivity and quarterly benchmark returns (r^b). The unit of observation is the fund-quarter. Regression samples include all funds where known commitments represent at least 5% of total fund commitments in Preqin. Quarterly NAV returns are winsorized at the 1% levels and are calculated as: log(NAV_{it}) - log($NAV_{i,t-1}$ - Cash Flow$_{it}$), where i indexes the fund and t indexes the quarter. Investor performance sensitivity is the average weight of the fund in its' investors' portfolios, fixed at the fund level. The benchmark is the FTSE Nareit U.S. Equity REITs index, which excludes mortgage REITs. The full set of controls includes; the size of the fund, whether the GPs of the fund raised a follow-on fund, quarterly capital calls, quarterly distributions, the percent called as of a given quarter, fund risk, fund HHI, GP reputation, and three measures of investor sophistication. Fund and investor controls are discussed in Section 3.5. Standard errors are clustered at the fund level. Test statistics are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.