How do private equity fees vary across public pensions?

Internet Appendix

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Abstract

In this appendix, we provide details about the underlying data used in the main text and discuss several quality checks that we perform on this data. We also document large within-fund dispersion in net-of-fee returns using several alternative return metrics that are popular within the private equity industry, including a return measure based only on realized cash distributions (DVPI). The pension effects documented in the main text are also strong when: (i) using DVPI to measure returns; (ii) flexibly adjusting for size and proxies for risk aversion; and (iii) controlling for pension expectations of private equity as an asset class. Finally, we show that *within* funds raised after 2010, pensions that have any mention of performance fees (carry) in their annual reports outperform those that do not.

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A Data

A.1 Source Description

The primary source of data that we use for this study comes from Preqin. Preqin is a data provider that specializes in alternative asset markets such as private equity and hedge funds. Preqin primarily sources their data from legally-required annual reports, Freedom of Information Act Requests (FOIA) request, and direct contact with investors and investment managers. For this reason, Preqin data mainly contains information on the investment behavior of public pension funds, especially U.S. public pension funds. Preqin has provided us with several different datasets on investor profiles and fund-specific characteristics. We base most of our measurement of within-fund return dispersion on a dataset that contains LP-level commitment amounts, contributions, cash flows, and reported remaining net-asset values (NAVs) into specific private-market funds, the largest of which are traditional private equity funds. At each point in time, we observe cumulative values for cash contributions and distributions to each fund. The raw data has information on funds whose vintage year ranges from 1969 to 2019, though we restrict our attention only to funds whose vintage is from 1990 onwards because the data is more populated and reliable starting in the 1990s.

A.2 Details on Data Processing

From the raw Preqin data, we create two cleaned datasets that we use in our analysis. The first is what we refer to as the *master sample* and the second is what we call the *core sample*. We now describe how we construct both datasets in more detail.

A.2.1 Master Sample

The unit of observation in the raw data is investor (p), fund (f), date (t), and source (s). There are a few instances where multiple investor-fund (p, f) cells have different sources, so we retain the source with the largest cell, after which the unit of observation is at the investor-fund-date level (p, f, t).

Before proceeding further, it is helpful to get a sense of coverage in the Preqin data. Specifically, for the U.S. public pensions in Preqin, we want to know how much of their overall private-market investment portfolio is covered in Preqin. To answer this question, we first annualize each investor-fund observation by taking the last observation within each year for each (p, f). This creates a sample that is unique at the investor-fund-year (p, f, y) level. Within each investor-year (p, y), we then sum the reported net-asset-value across all observations in the year. This gives us a sense of the total value invested in private markets according to Preqin. We then merge each pension-year estimate with the associated amount invested in private equity and real estate according to data from the Public Plans Data from the Center for Retirement Research at Boston College. For the matched Preqin-PPD annual investment amounts, we then aggregate by year and across investors. Figure A.1 summarizes this exercise for the period 2001-2017, which is the length of the PPD data. The blue bars show the total amount invested in PE and real estate according PPD and the red bar shows what percent of this total is observed in Preqin. Again, the figure is made only for the pensions that are in both the Preqin and PPD datasets in a given year. The two main takeaways from the plot are as follows: (i) the public pensions in Preqin account for a significant fraction of aggregate pension investment into PE and real estate, which in 2017 totaled roughly \$900 billion (Begenau and Siriwardane, 2020b); and (ii) for public pensions in Preqin, we observe a fairly large portion of their overall investment into PE and real estate. For example, in the later years of the sample, we consistently observe at least 60% of their entire portfolio at a granular level in Preqin. This estimate likely understates the coverage in Preqin because not all real estate investment in PPD is done through PE-like structures, which is all we would observe in Preqin.

After removing multiple sources for the same investor-fund cell, we then apply several additional filters to the data. We drop any fund f whose reported valuation currency is not in USD (6.2%). In addition, we drop co-investments by excluding funds whose category type in Preqin is listed as "Co-Investment Multi-Manager", "Co-investment", or "Real Estate Co-Investment". In addition, we drop any fund whose name contains the phrase "Co-", which in our manual search of the data removes any obvious coinvestment funds (all co-investment filters represent 1.2% of total observations). Finally, given our focus on U.S. public pension funds, we only retain investors whose geography is listed by Preqin as U.S. and drop observations where Preqin lists the investor type as Foundation, Insurance Company, or Private Sector Pension Fund. After applying these filters, the remaining investor types are 90.77% Public Pension Fund, 7.25% Endowment Plan, 1.81% Sovereign Wealth Fund, and 0.17% Government Agency. We have verified that all of the Endowment Plans are for state universities, which is why we chose to include them in our subsequent analysis. Similarly, we have verified that the investors listed as Sovereign Wealth Funds or Government Agency all correspond to the investment boards of U.S. public defined-benefit pension funds.

From here, we further screen the data based on the procedure described in Section 2.3 of the main text. As a reminder, this procedure eliminates observations with missing return data and where we deem within fund-date (f,t) returns to be implausibly large. We then create a quarterly dataset by taking the last investor-fund-date observation within each quarter, dropping observations where the year of observation is not at least one year after the fund's vintage. As discussed in the main text, this is done to avoid any accounting issues that may be present with younger funds (e.g., when capital has been called but not deployed). To avoid stale or erroneous data, we also drop all investor-fund cells where the year of the first reported return by investor p in fund f is more than

2 years before the fund's reported vintage year.

Finally, when possible we merge the cleaned Preqin data with several outside data sources. We obtain the overall size of each pension in a given year by looking in PPD, a separate investor-profile dataset provided by Preqin, hand-collected data on pension size, and then data on size from Andonov et al. (2018), in that order.[1] We also merge the cleaned Preqin data on board composition from Andonov et al. (2018), the latter of which we have augmented with hand-collected data from 2013 onwards. Overall, this cleaning and merging process leaves us with 287,709 investor-fund-quarter observations. which is what we call the *master sample*.

A.2.2 Core Sample

While the master sample is unique at the investor-fund-quarter level, the *core sample* is unique at the investor-fund level. The core sample is designed so that we have maximal power to study within-fund return dispersion, which we argue in the main text is most likely driven by within-fund dispersion in fees. Specifically, define n_{ft} as the number of investors reporting returns – measured using TVPI or the total multiple on invested capital – in fund f at quarter t. We first drop all fund-quarter cells where $n_{ft} < 2$, as this is a necessary requirement to compute within-fund return dispersion. Next, for fund f, define the set of dates $T_f = \arg\max_t n_{ft}$ where we observe the most investors reporting returns for fund f in the same quarter t. For this subset of dates, we retain only observations for fund f on the latest date $t_{f,max} = \max T_f$. In other words, for each fund f, we find the latest possible quarter such that the maximum number of investors report returns for the fund in that quarter. We do so to ensure any differences in fees across investors have adequate time to appear in the data in the form of within-fund return dispersion. For example, if investors in a given fund all pay different management fee, then such differences will be easier to detect if they have accumulated over 10 years as opposed to over 1 year. In the main text, this is why we use the core sample to compute various measures of within-fund return dispersion and to estimate whether some pensions consistently outperform others in the same fund (i.e., pension effects).

A.2.3 Internal Rates of Return (IRRs)

Our analysis in the main text primarily relies on TVPI to measure returns in private market investment vehicles. TVPI is the simplest possible measure of returns, as it is defined at each point in time as the total amount of capital received by the investor plus the net-asset value of any remaining investments in the fund, all scaled by the total amount of capital contributed by the investor. Because it is effectively the cumulative return on capital, TVPI is often called the multiple on invested capital within the private equity industry. DVPI is defined in an analogous fashion, except

[1] We are very grateful to Josh Rauh for sharing the data on size and board composition with us.

it only reflects the total amount of capital received by the investor and excludes any remaining net-asset value.

Another popular metric in the industry is the internal rate of return (IRR). Preqin provides what we call a "reported IRR" as one of their data fields, which comes from both their internal calculations and IRRs that get reported to them by individual investors. An important limitation of the reported IRRs is that they are rounded to two decimals (they are reported in percentage points), which makes a reliable computation of within-fund return dispersion less accurate. Another reason that IRRs are problematic for our setting is that they are notoriously sensitive to the timing of cash flows and in the context of PE have been shown to be more prone to manipulation. For example, Andonov et al. (2018) find that cash flow data in Preqin is more likely to be missing for lower performing PE funds, thus making a reliable calculation of IRR much more difficult. And, in our inspection of the data, we have found several instances where reported IRRs are annualized in the early years of a fund's life but is not in later years, or vice versa. For all of these reasons, we prefer TVPI or DVPI to IRRs because they are simple to compute and arguably more reliable measures of return.

With that said, in this appendix we provide several robustness checks using IRRs, using both reported and what we refer to as manually-computed IRRs. For each investor p in fund f at time t, we manually compute annual IRRs using the observed sequence of cash inflows (including remaining net-asset values) and outflows up to time t. In cases where there are missing cumulative distributions for p in fund f, we linearly interpolate between a maximum of two missing distributions. We do the same for cumulative contributions and net-asset values. Using this data, we only compute an IRR if net inflows are negative for at least one date before t.

We then drop the 1% tails of the manually-computed IRR distribution in order to mitigate the impact of outliers. In addition, because IRRs are most accurate for a continuous sample of cash flow data, we replace the manually-computed IRRs with reported IRRs in two cases: (i) more than 30% of the quarters between the first observed return for p in f and date t are missing; and (ii) the year of the first observed return for p in f is more than 2 years after the fund's reported vintage. In cases where we cannot actually compute an IRR, we also replace it with Preqin's reported IRR.

Manually computing IRRs in the preceding fashion delivers a non-negligible improvement over reported IRRs in terms of missing data. In the master sample, 15.4% of observations do not have a reported IRR in Preqin whereas only 6.8% are missing manually computed IRRs (none are missing TVPI and DVPI by construction). In the core sample, 19.1% of observations are missing a reported IRR compared to 8.7% for manually-computed IRRs. And, in the subset of the master data where we have both a reported and manually-computed IRR, the two line up reasonably well. Figure A.2 shows this visually via a binned scatter plot of the manually-computed IRRs against the IRRs reported in Preqin. The plot shows a strong linear relationship between the two series. Reassuringly, the estimated slope coefficient when regressing manually-computed IRRs on reported IRRs is 1.01, indicating the two move in lockstep in the master sample. However the estimated intercept of -43 basis points suggests that reported IRRs are potentially inflated by a constant amount, which is another reason we prefer to use TVPI as our primary measure of returns.

A.3 Additional Quality Control

The focal point of this study is within-fund dispersion in returns. Naturally, dispersion will be increasing with any noise in the data, so we have performed several quality checks to minimize any such bias in our analysis. First, and most importantly, we use an economically-driven filtering procedure that drops fund-date cells with implausibly high TVPI dispersion (see Section 2.3 for details). Second, we check whether the various return measures are all highly correlated: in raw levels, TVPI is 91% correlated with DVPI, 70% correlated with reported IRRs, and 65% correlated with manually-computed IRRs. The fact that TVPI is more correlated with DVPI than either IRR measure is consistent with our argument that IRRs are often less reliable return metrics in the context of private markets (see Section A.2.3). Figure A.3 uses a binned scatter plot to show the correlation of TVPI with reported IRRs (Panel A) and DVPI (Panel B). In both instances, we demean all variables within fund-quarter to align more naturally with the concept of within-fund return dispersion. In Panel A, there is a clear positive, albeit non-linear relationship between TVPI and reported IRRs. The non-linear relationship is natural given the definition of IRR. Panel B shows a strong and linear relationship between DVPI and TVPI. Overall, the simple fact that these various return metrics are all correlated provides some comfort that our data is of reasonably high quality.

The strong relationship between TVPI and DVPI is particularly important because NAV accounting does not explain why some investors outperform other investors within the same fund-quarter. DVPI is based purely on distributed cash flows to investors and is harder to manipulate because all U.S. pensions face a minimum set of compliance and reporting requirements. For example, public pensions must file audited annual reports that report cash inflows and outflows of the entire pension, of which DVPI would naturally be a component. More broadly, the fact that the underlying Preqin data is based on audited financial reports and FOIAs is another reason that the data is likely of high quality.

The correlation between TVPI and DVPI also has important important implications for the pension effects that we document in Section 4.1. To see why, recall that the pension effects we find imply that some pensions consistently outperform others in the same fund, at least in terms of TVPI. However, if certain pensions report NAVs differently than others, than the pension effects could be driven by these accounting differences, as opposed to actual return differences. This could be true even if we observe strong pension effects using DVPI (Section B.3), as the pensions who consistently outperform in TVPI terms may not necessarily be those that do in DVPI terms. To show that this is not the case, we separately regress TVPI and DVPI on fund fixed-effects using the core sample. This is equivalent to demeaning both within each fund. We then compute the average residual TVPI and DVPI for each pension in the sample and plot the resulting pension-level series in Figure A.4. The scatter plot shows that the resulting two series are highly correlated (71%). Thus, pensions that *consistently* outperform others in the same fund in TVPI terms also do so in DVPI terms. This analysis also acts as another quality check of the data.

B Supplementary Analysis

In this section, we present the following results that complement our analysis in the main text: (i) relative to the full sample, potential aggregate gains are comparable for a subsample of investors and funds that are less likely to have co-investment rights and other investor-specific mandates; (ii) within-fund return dispersion is large when using IRRs to measure returns; (iii) within-fund pension effects are statistically and economically significant when using DVPI instead of TVPI; (iv) akin to the estimated pension effects, certain pensions are more likely to be bottom tercile performs than others when investing in a given fund; and (v) within funds raised after 2010, pensions that don't report performance fees or carry in their annual reports perform worse than investors that do track these costs.

B.1 Potential TVPI Gains Prior to 2010

Throughout the study, we interpret within-fund dispersion in net-of-fee returns as evidence of price discrimination – pensions pay different fees for exposure to the same gross fund exposure in private markets. This interpretation hinges on the assumption that the net-of-fee returns that we observe all reflect claims to the same gross fund exposure. In the language of our accounting framework from Section 2.2, the cumulative net-of-fee return for investor p at time t in fund f is:

$$r_{pft} = g_{pft} + \varepsilon_{pft} - c_{pft},$$

where g_{pft} is the gross return of fund f that is common to all investors in our data, ε_{pft} are any deviations from this shared gross return, and c_{pft} are investor-specific costs or fees. Our identifying assumption is therefore that ε_{pft}. This assumption would be violated if, for example, our return data reflects co-investment arrangements or other investor-specific mandates (e.g., ESG).

We argue in Section 3.4.3 that $\varepsilon_{pft} \approx 0$ is likely to hold true in our data for several reasons, the most important being that co-investment returns do not appear to be bundled with our return data. In addition, we now measure within-fund return dispersion using a subsample of investors and funds where co-investment and other investor-specific mandates are unlikely to exist at all. Specifically, we compute potential aggregate gains from within-fund return dispersion excluding large pensions (over \$100 billion in assets) and only for funds with a vintage year prior to 2010. $\varepsilon_{pft} \approx 0$ is more likely in this sample because smaller pensions do not typically have the infrastructure to co-invest and contractual features like ESG-mandates were not popularized until after the 2008 Global Financial Crisis.

Table A.1 presents estimates of potential gains for this subsample of data. As a reminder, we define potential gains for investor p in fund f by comparing p's return – measured in TVPI or DVPI – to the maximum return in the fund. We then aggregate by weighing potential gains by the size of investment. The table shows gain estimates after imposing additional restrictions on the subsample, such as age and how we define comparison groups when computing investor-level potential gains. The main takeaway is that aggregate potential TVPI gains in this subsample are broadly consistent with those estimated using all investors and funds (Table 2) in the core sample. When looking at non-liquidated funds, the average potential gain estimate when restricting attention to smaller pensions in funds prior to 2010 is about \$7.70 per \$100 invested, compared to \$8.50 when using the entire core sample. The same pattern emerges when comparing potential gains using DVPI and excess gains using TVPI. Thus, we conclude that the within-fund return dispersion that we document in this study is most likely due to price (fee) discrimination.

B.2 Potential IRR Gains due to Fee Dispersion

For robustness, Table A.2 contains estimates of aggregate potential and excess gains using manually-computed IRRs instead of TVPI to measure returns. Consistent with our results using TVPI, we once again observe large within-fund return dispersion in the form of potential gains. For example, even when looking at fully liquidated funds, investors would have earned roughly 2.4% more in annual IRR had they each received the best ex-post fee contract in their respective funds. Again, best in this context is defined based on the highest performing investor that we *observe* in the fund, meaning potential gains due to within-fund fee dispersion could be even higher in reality. For liquidated funds, excess IRR gains – which represent a lower bound on redistribution due to within-fund fee dispersion – are also large, ranging from 1.88% to 2.27% per year. The estimates in columns (3)-(11) are based on a broader sample that includes non-liquidated funds. Here, potential IRR gains are roughly 1.64%, so a bit lower than in liquidated funds but nonetheless substantial.

Table A.3 repeats the analysis using the IRRs reported to us in Preqin, as opposed to those that we manually-compute. Potential and excess gains in reported IRRs are noticeably lower than when we use manually-computed IRRs. Part of this pattern likely occurs because reported IRRs are missing more often in the data, as evidenced by the fact that the sample sizes in Table A.3 are smaller than in Table A.2. More importantly, and as discussed more extensively in Section A.2.3, reported IRRs are rounded in the data and more prone to manipulation by investors. With that said, the average potential IRR gain when using reported data is still roughly 73 basis points per year for non-liquidated funds, which is large when considering such within-fund return differences compound over the life of the private-market fund (typically 10-15 years).

B.3 Analysis using DVPI

In this subsection, we repeat the main components of our analysis using DVPI to measure returns instead of TVPI. The difference between the two return metrics is that DVPI only reflects realized cash distributions received by the investor, whereas TVPI reflects both cash distribution and unrealized liquidation value. Figure A.3 above shows that DVPI and TVPI are highly correlated. Nevertheless, we redo our analysis with DVPI as return measure to address the concern that TVPI is distorted by how GPs or pensions measure and report NAVs.

Potential DVPI Gains due to Fee Dispersion Table A.4 shows estimates of aggregate potential and excess gains using DVPI. In liquidated funds, investors would have earned about $4.50 more in DVPI per $100 invested had they each received the best ex-post fee contract in their respective funds. This estimate is extremely close to the one we obtain in liquidated funds when using TVPI (see Table 2), which is not surprising because DVPI and TVPI should be effectively equal for liquidated funds.[2] When looking at non-liquidated funds in columns (3)-(11), the average potential DVPI is $6.74 per $100 invested, which is lower than the estimate of $8.50 that we obtain when using TVPI. The fact that within-fund DVPI dispersion – and hence aggregate potential gains – are lower when using DVPI is also not surprising because any fee differences across investors should be more pronounced when considering unliquidated NAVs.

We observe similar patterns when quantifying within-fund return dispersion with excess gains, as opposed to potential ones. Recall that excess gains are based on a comparison investor p's return in fund f with that of the minimum return. Thus, unlike our potential gain measure, the excess gain metric does not rely on the assumption that the fund generates enough surplus to allow for all pensions to have earned the maximum returns. Instead, our excess gain measure captures is guaranteed to be budget feasible and is a lower bound on the redistribution that occurred within

[2]The two are not identical because of how we construct the core sample. The status of a fund in Preqin is listed as of June 2019, the month in which the data was delivered to us. When we construct the core sample, we choose the observation date such that the most number of investors are present, which may not always coincide with the last date in the sample. Thus, in the core sample, the observation date for funds listed as liquidated may nonetheless have a small amount of non-liquidated assets. Importantly, when imposing fund age restrictions in our analysis, we use the observation date.

the fund due to fee differences. The broader overall point here is that we still observe fairly large within-fund return dispersion when measuring returns using DVPI.

Pension Effects Using DVPI Next, we repeat our analysis from Section 4.2 by estimating the following regression on the core sample:

$$\delta_{pf} = \alpha_f + \theta_p + \varepsilon_{pf}$$

where δ_{pf} is the DVPI of investor p in fund f, α_f are fund fixed effects, and θ_p are investor fixed effects (i.e., so-called pension effects). The objects of interest in this regression are the pension effects θ_p, which tell us whether some pensions consistently earn higher DVPIs than other pensions in their respective funds. Formally, we test whether this is the case using an F-test of the null hypothesis that the θ_p's are jointly equal. Panel A of Table A.5 summarizes these F-tests on the sample of funds that are at least 1, 4, and 8 years old. Regardless of the subsample, the we consistently reject the null that the θ_p's are jointly equal with p-values of less than 1%. This is true when we use parametric p-values or non-parametric ones generated using the permutation tests described in Section 4.1.1.

Panel B of Table A.5 provides a sense of the economic magnitude of the pension effects. We again shrink the estimated pension effects based on their standard errors using the procedure described in Section 4.1.1. In funds that are at least 8 years old, moving from the 20th to 80th percentile in terms of pension quality – as measured by the pension effects – is worth an average of 366 basis points of DVPI within the same fund. The size of this pension effect compares favorably to the magnitude that we obtain when using TVPI. Overall, this analysis shows that there are economically large and statistically significant pension effects when using either DVPI or TVPI. Moreover, as we showed in Section A.3, the pensions that consistently outperform others in their respective funds based on DVPI are also those that do based on TVPI.

B.4 Pension Effects with Full Characteristic Adjustment

In Section 4.3, we explore a few ways to quantify how much observable characteristics can explain the pension effects that we document in Section 4.1. We do so via the following fixed-effects regression:

$$r_{pf} = \alpha_f + \theta_p + \beta X_{pf} + \varepsilon_{pf}$$

where r_{pf} is the TVPI of investor p in fund f, α_f is a fund-fixed effect, and θ_p is a pension fixed-effect. The set of characteristics X_{pf} that we consider are taken from Section 4.2. We now expand the set of characteristics that we adjust for as follows. First, instead of including an indicator variable for whether a pension's AUM exceeds $100 billion, we sort pensions into quintiles based on their AUM in a given vintage year. We then include a full set of dummy variables associated with each pension's size quintile in a given vintage year. Second, as a proxy for risk aversion, we include the share of cash in pension p's portfolio in the vintage year of fund f. The number of pensions for which we can estimate pension effects shrinks considerably when including this variable because it comes from the PPD database, and PPD does not cover all of the pensions in the Preqin sample.

Panel A of Table A.6 summarizes F-tests of the equality of pension effects θ_p, after controlling for the aforementioned pension characteristics. Regardless of the age of funds that we consider, we continue to reject the null hypothesis of no pension effects. Panel B of Table A.6 confirms that the estimated characteristic-adjusted pension effects are both statistically and economically meaningful. Importantly, this means that some pensions consistently outperform others in their respective funds after flexibly accounting for size, a proxy for risk aversion, relationships, etc.[3] The flexible controls for size should presumably account for any differences in marginal cost across pensions from the perspective of the GP. And, our proxy for risk aversion helps rule out the possibility that our pension effects are due to the fact that some pensions systematically choose fee structures based on risk preferences.

B.5 Expectations of Private Equity Performance

In Section 5, we consider several different mechanisms that might generate within-fund fee dispersion. One such mechanism is that pensions are willing to pay different fees for access to the same fund because they have different expectations about the gross return of the fund. While we do not have investor-fund level data on expectations, after 2014 pensions do report their expectations of private equity on comprehensive annual report (Andonov and Rauh, 2019). As an imperfect way to test whether expectations can explain fee dispersion, we run the following sequence of regressions:

$$r_{pf} = \alpha_f + \beta e_{pf} + \varepsilon_{pf}$$
$$r_{pf} = \alpha_f + \theta_p + \beta e_{pf} + \varepsilon_{pf},$$

where e_{pf} is the expected return on private equity as listed by investor p in the vintage year of fund f, meaning that this variable does not vary across funds of the same vintage. α_f is a fund fixed effect. The first regression checks whether within-fund variation in returns lines up with variation in PE return expectations. The second re-runs the first regression with pension fixed effects θ_p, which then allows us to test whether the pension effects are present in this subsample

[3]In unreported results, we find similar conclusions when proxying for risk aversion using the target share of fixed income of pension p in the vintage year of fund f.

after controlling for PE return expectations. Given the short sample of return expectations, we also run the two regression for the set of funds whose minimum observed TVPI is above 1 in order to generate more power by allowing any potential differences in carry across investors to appear.

Table A.7 shows that pension funds that report higher return expectations of PE as an asset class are not those that pay higher fees within a given fund. Though the point estimate in the regression is negative, it is economically small and statistically insignificant. In addition, when we include pension fixed effects in the regression we continue to reject the null that fee contracts are randomly assigned within funds (i.e., pension effects). Thus, reported return expectations do little to explain why some pensions systematically pay more than others when investing in the same fund. However, as previously noted, it is difficult to draw broad conclusions from this analysis because we have a short sample and return expectations are at the asset class level, not the fund level.

B.6 Reporting of Performance Fees

We show in Section 4.4 that within-fund differences in carry are an important way in which GPs charge LPs different fees. Motivated by this finding, we then search the comprehensive annual reports for the pensions in our sample over the period from 2010 to 2018, a period in which comprehensive annual reports were most readily available online. We specifically look for any mention of carry or performance fees in the annual reports. Puzzlingly, only 7% of the plans in our sample have any mention of performance fees or carry on their annual reports. This simple fact begs the question of whether public pension funds fully internalize carry as an important cost?

To explore this question in the data, we run the following regression:

$$r_{pf} = \alpha_f + \beta X_{pf} + \theta 1_{pf}\{\text{Reports Carry}\} + \varepsilon_{pf}$$

where r_{pf} is the TVPI of investor p in fund f and X_{pf} is the vector of observable characteristics described in Section 4.2. $1_{pf}\{\text{Reports Carry}\}$ is a dummy variable that is one if pension p has *any* mention of carry or performance fees on its annual report in fund f's vintage year. As before, the fund fixed effect α_f means that we are comparing TVPI across investors in the same fund.

Table A.8 presents OLS estimates of the regression for funds of at least 1 and 3 years of age, conditional on the fund's vintage being after 2010. In univariate regressions of TVPI on the carry-indicator we find that within a given fund, pensions that mention carry on their annual reports outperform those that do not (Columns 1 and 3). Though highly suggestive, this result is consistent with the idea that some pensions do not fully internalize carry as an investment cost and therefore do not report it as such on their annual reports. Consequently, these pensions then pay higher fees – likely in the form of carry – when investing in private markets. Indeed, we have contacted several pensions directly to inquire about the amount of performance fees that they pay and have frequently been told that they do not keep track of carry because it is automatically taken out of cash distributions by the GP. However, we want to emphasize that this analysis should be interpreted with caution, especially given that it is run on a relatively short sample. With that said, to the extent that the reporting of carry is a measure of sophistication, the fact that the point estimate on the carry-indicator shrinks in Columns (2) and (4) implies that sophistication is correlated with size and being an early investor.

Taking a step back, it is perhaps not surprising that pensions would not fully internalize the ex-ante costs of carry. A convenient way to think about the carry component of the fee structure is that LPs write the GP a call option on the gross return of the fund, with strike price set at 1 in terms of cumulative returns. Due to its option-like nature, the ex-ante value of carry is harder to compute relative to management fees. To see why, note that valuing the carry component requires an estimate of fund-level volatility. However, given that there is no consensus on the risk properties of private equity as an asset class (Harris et al., 2014; Ang et al., 2018; Stafford, 2017), generating a fund-level estimate of volatility and then applying the appropriate option-pricing model seems like a difficult problem for any investor to solve.

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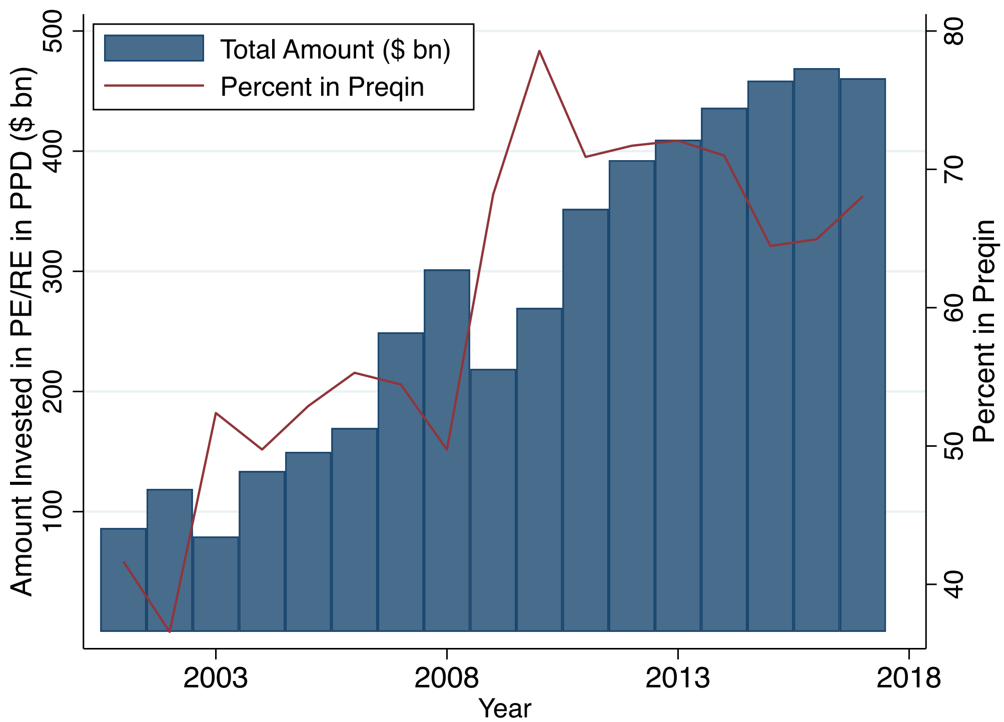
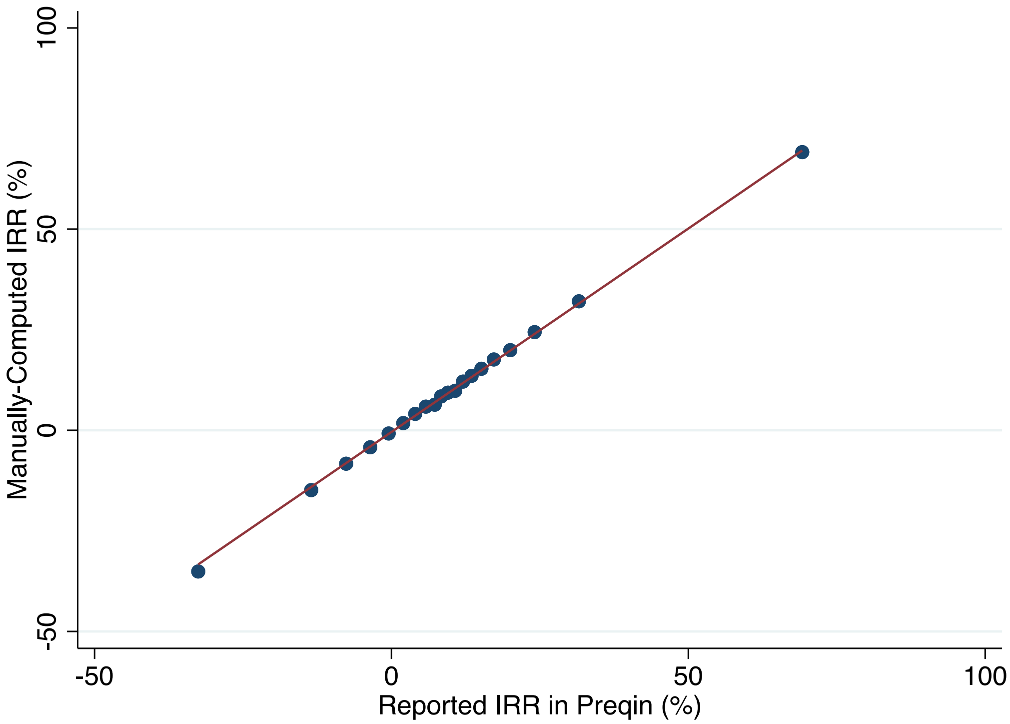
Figure A.1: Preqin Investment Coverage



Notes: The blue bars in the figure plot the end-of-year total net-asset-value across all U.S. public pensions in the Preqin dataset. For each U.S. public pension in Preqin, we find the associated amount invested in private equity and real estate according to according to the Public Plans Data (PPD) from the Center for Retirement Research at Boston College. The red line in the figure shows the ratio of the end-of-year total net-asset-value across all pensions in Preqin to the total reported amount invested in PPD. All calculations are reported only for the matched Preqin-PPD sample (at the investor-year level).

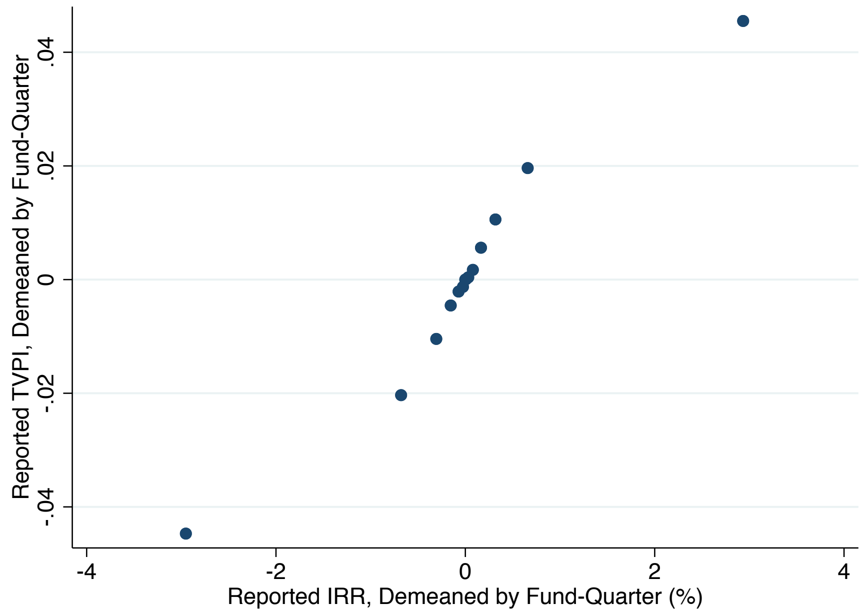
Figure A.2: Manually-Computed versus Preqin-Reported IRR



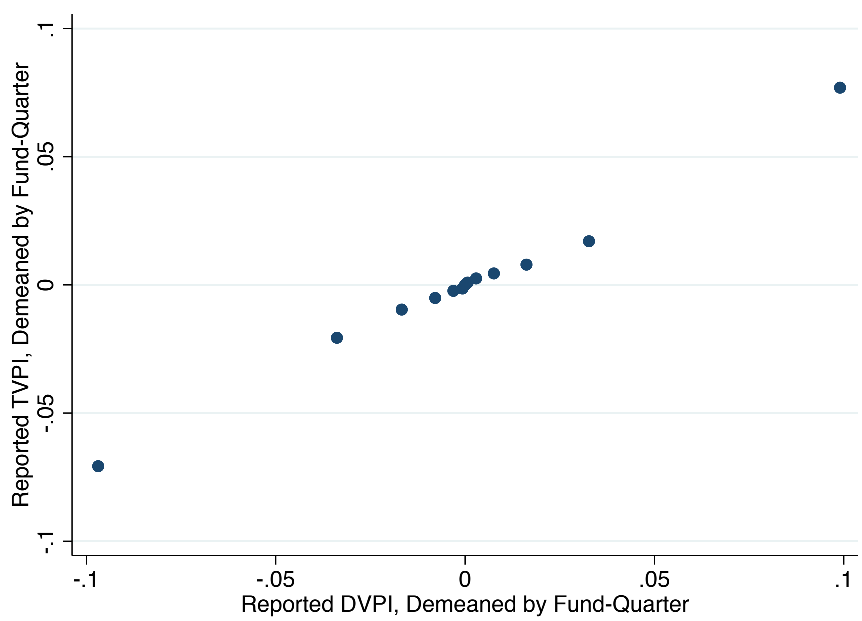
Notes: This figure shows manually-computed IRRs based on observed cash flows in Preqin against IRRs that are directly reported in Preqin. See Section A.2.3 for details on how we manually compute IRRs.

Figure A.3: Correlation of Different Return Measures

Panel A: TVPI vs Reported IRR

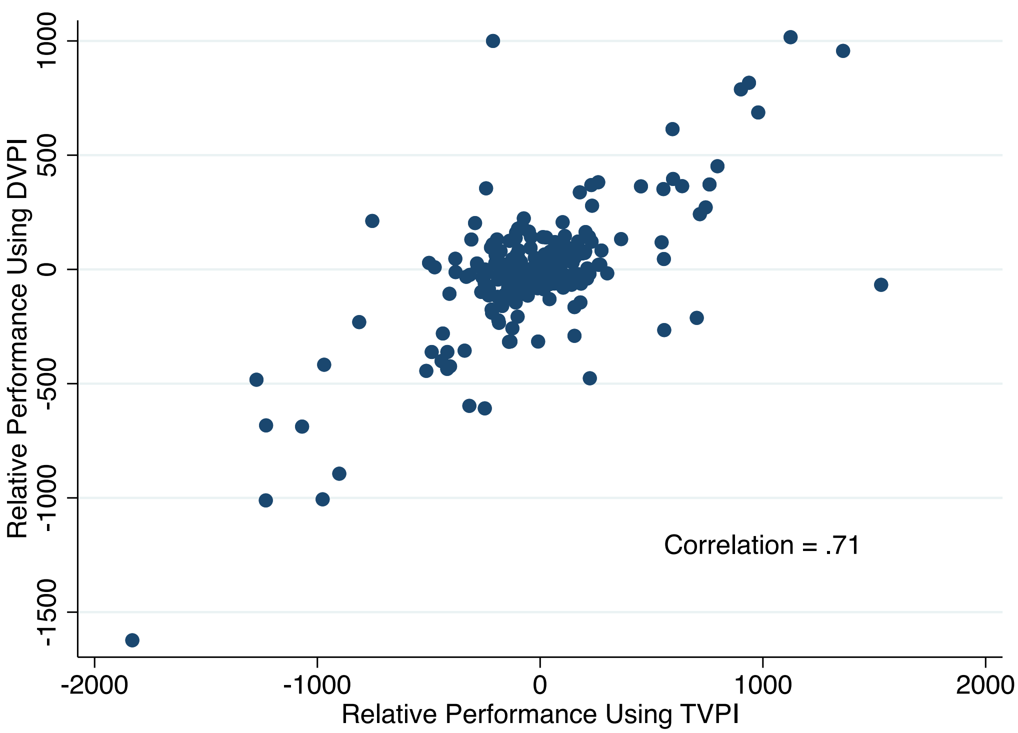


Panel B: TVPI vs DVPI



Notes: Panel A of the plot is a binned scatter plot of TVPI against reported IRRs. Panel B is a binned scatter plot of TVPI versus DVPI. For both plots, all variables are demeaned within fund-quarter before plotting. Data for the plot is from the master sample (see Section A.2.1).

Figure A.4: Pension Effects using TVPI versus DVPI



Notes: This figure shows pension-level measures of relative within-fund performance using TVPI and DVPI. To create the plot, we separately regress TVPI and DVPI on fund fixed-effects and save the residuals. For each residual series, we then average within pension and plot the resulting pension-level estimates against each other. See Section A.3 for more detail.

Table A.1: Potential Return Gains Due to Fee Differences, Smaller Pensions Prior to 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
TVPI Potential Gain (of % invested)	4.89	4.73	6.98	6.87	6.74	6.86	6.76	6.67	9.94	9.76	9.16
DVPI Potential Gain (of % invested)	4.75	4.72	5.48	5.25	5.01	5.41	5.24	4.90	8.17	7.89	7.01
TVPI Excess Gain (of % invested)	2.25	2.24	2.98	3.17	2.87	3.00	3.18	2.91	3.74	3.91	3.66
Amount Invested ($ bn)	18	19	98	113	120	103	118	126	202	230	238
Total *N*	435	485	1,644	1,911	2,143	1,766	2,045	2,306	4,594	5,194	5,695
Number of Funds	143	161	466	532	585	497	566	620	1,198	1,343	1,481
Number of Investors	58	63	102	115	128	107	118	130	173	184	199
Sample Restrictions:											
Years Since Inception	10	10	10	8	4	10	8	4	10	8	4
Fund	×	×	×	×	×	×	×	×	×	×	×
First Contribution Month	×		×	×	×						
Last Report Month	×		×	×	×						
First Contribution Quarter		×				×	×	×			
Last Report Quarter		×				×	×	×	×	×	×
Liquidated	×	×									

Notes: This table presents several measures of within-fund fee dispersion based on core sample, with the additional restriction that we focus only on smaller pensions investing in funds raised prior to 2010. Smaller funds are defined as those with less than $100 billion in assets. To generate the first row of the table, we compute the incremental return gain (measured in TVPI) for investor p in fund f if it had earned the best observed return in the fund. The potential dollar return gain is simply the incremental return gain for each investor $p$multiplied by its contribution to fund f. We aggregate by summing potential dollar gains and then scaling by the total amount of contributed capital across investors. The second row is the same measure using DVPI instead of TVPI to measure returns. The third row is an analogous calculation, but we instead compute each investor's excess gain in fund f as the difference between their actual return (measured in TVPI) and the lowest observed return in the fund. The remaining rows provide summary statistics and details on the subsample that we use to compute these metrics. The subsample restrictions that refer to the first and last contribution dates (either month or quarter) describe how we compute the maximum or minimum observed within-fund return. For example, when the restriction on the first contribution month means that we only compare investors whose first observed contribution month in the data is the same. See Section 3 for a complete discussion.

Table A.2: Potential Return Gains Due to Fee Differences: Manually-Computed IRRs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Potential IRR Gain (%)	2.44	2.43	1.39	1.34	1.44	1.39	1.33	1.44	2.11	2.10	2.24
Excess IRR Gain (%)	1.88	2.27	1.00	0.80	0.85	1.07	0.86	0.89	1.35	1.13	1.12
Amount Invested ($ bn)	26	27	148	177	272	154	183	281	270	314	440
Total N	528	578	2,003	2,488	4,168	2,131	2,629	4,387	4,975	5,882	8,478
Number of Funds	174	191	541	665	1,018	571	695	1,060	1,280	1,498	2,070
Number of Investors	56	58	99	115	136	102	117	139	163	173	203
Sample Restrictions:											
Years Since Inception	10	10	10	8	4	10	8	4	10	8	4
Fund	×	×	×	×	×	×	×	×	×	×	×
First Contribution Month	×		×	×	×						
Last Report Month	×		×	×	×						
First Contribution Quarter		×				×	×	×			
Last Report Quarter		×				×	×	×	×	×	×
Liquidated	×	×									

Notes: This table presents several measures of within-fund fee dispersion based on the core sample. To generate the first row of the table, we compute the incremental return gain (measured in manually-computed IRR) for investor p in fund f if it had earned the best observed return in the fund. The potential dollar return gain is simply the incremental return gain for each investor $p$multiplied by its contribution to fund f. We aggregate by summing potential dollar gains and then scaling by the total amount of contributed capital across investors. The second row is an analogous calculation, but we instead compute each investor's excess gain in fund f as the difference between their actual return (measured in manually-computed IRR) and the lowest observed return in the fund. The remaining rows provide summary statistics and details on the subsample that we use to compute these metrics. The subsample restrictions that refer to the first and last contribution dates (either month or quarter) describe how we compute the maximum or minimum observed within-fund return. For example, when the restriction on the first contribution month means that we only compare investors whose first observed contribution month in the data is the same. See Section 3.1 for a complete discussion of how we measure potential and excess gains and Section A.2.3 for how we manually compute IRRs.

Table A.3: Potential Return Gains Due to Fee Differences: Reported IRRs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Potential IRR Gain (%)	0.37	0.36	0.47	0.46	0.57	0.48	0.47	0.58	1.05	1.24	1.24
Excess IRR Gain (%)	0.23	0.23	0.22	0.25	0.32	0.23	0.25	0.32	0.41	0.45	0.47
Amount Invested ($ bn)	26	27	143	170	256	149	175	264	260	302	417
Total *N*	508	559	1,905	2,362	3,867	2,023	2,487	4,048	4,770	5,623	7,947
Number of Funds	171	189	525	645	977	554	672	1,014	1,256	1,469	2,010
Number of Investors	52	54	91	106	123	93	108	127	155	164	193
Sample Restrictions:											
Years Since Inception	10	10	10	8	4	10	8	4	10	8	4
Fund	×	×	×	×	×	×	×	×	×	×	×
First Contribution Month	×		×	×	×						
Last Report Month	×		×	×	×						
First Contribution Quarter		×				×	×	×			
Last Report Quarter		×				×	×	×	×	×	×
Liquidated	×	×									

Notes: This table presents several measures of within-fund fee dispersion based on the core sample. To generate the first row of the table, we compute the incremental return gain (measured in IRRs reported in Preqin) for investor p in fund f if it had earned the best observed return in the fund. The potential dollar return gain is simply the incremental return gain for each investor $p$multiplied by its contribution to fund f. We aggregate by summing potential dollar gains and then scaling by the total amount of contributed capital across investors. The second row is an analogous calculation, but we instead compute each investor's excess gain in fund f as the difference between their actual return (measured in IRRs reported in Preqin) and the lowest observed return in the fund. The remaining rows provide summary statistics and details on the subsample that we use to compute these metrics. The subsample restrictions that refer to the first and last contribution dates (either month or quarter) describe how we compute the maximum or minimum observed within-fund return. For example, when the restriction on the first contribution month means that we only compare investors whose first observed contribution month in the data is the same. See Section 3.1 for a complete discussion of how we measure potential and excess gains and Section A.2.3 for a discussion of IRR measures.

Table A.4: Potential Return Gains Due to Fee Differences: DVPI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
DVPI Potential Gain (of % invested)	4.51	4.46	7.52	6.06	4.67	7.42	6.03	4.65	8.99	8.47	6.83
DVPI Excess Gain (of % invested)	2.16	2.20	2.88	2.66	2.23	2.89	2.68	2.23	3.38	3.24	2.82
Amount Invested ($ bn)	27	29	157	186	285	163	193	295	288	335	471
Total N	558	615	2,099	2,600	4,384	2,238	2,754	4,622	5,396	6,363	9,235
Number of Funds	178	197	554	680	1,054	586	713	1,099	1,357	1,589	2,228
Number of Investors	64	68	107	125	152	111	126	154	176	190	230
Sample Restrictions:											
Years Since Inception	10	10	10	8	4	10	8	4	10	8	4
Fund	×	×	×	×	×	×	×	×	×	×	×
First Contribution Month	×		×	×	×						
Last Report Month	×		×	×	×						
First Contribution Quarter		×				×	×	×			
Last Report Quarter		×				×	×	×	×	×	×
Liquidated	×	×									

Notes: This table presents several measures of within-fund fee dispersion based on the core sample. To generate the first row of the table, we compute the incremental return gain (measured in DVPI) for investor p in fund f if it had earned the best observed return in the fund. The potential dollar return gain is simply the incremental return gain for each investor $p$multiplied by its contribution to fund f. We aggregate by summing potential dollar gains and then scaling by the total amount of contributed capital across investors. The second row is an analogous calculation, but we instead compute each investor's excess gain in fund f as the difference between their actual return (measured in DVPI) and the lowest observed return in the fund. The remaining rows provide summary statistics and details on the subsample that we use to compute these metrics. The subsample restrictions that refer to the first and last contribution dates (either month or quarter) describe how we compute the maximum or minimum observed within-fund return. For example, when the restriction on the first contribution month means that we only compare investors whose first observed contribution month in the data is the same. See Section 3.1 for a complete discussion of how we measure potential and excess gains.

Table A.5: Pension Effects on Within-Fund DVPI

Panel A*: *Statistical Tests of Pension Effects

	Dependent Variable: DVPI (bps)				
	Pension-Effects				
Min. Fund Age	F	p	p^*	K	N
1	2.59	<0.01	<0.01	228	10,879
4	2.65	<0.01	<0.01	222	8,532
8	3.28	<0.01	<0.01	179	4,948

Panel B*: Size Distribution of Estimated Pension Effects*

	DVPI (bps)				
Min. Fund Age	Std. Dev	p60-p40	p80-p20	p90-p10	p95-p5
1	256	39	167	420	721
4	338	44	212	498	868
8	500	98	366	673	1,117

Notes: Panel A of the table shows regressions of the form $d_{pf} = \alpha_f + \theta_p + \varepsilon_{pf}$, where d_{pf} is the DVPI of pension p in fund f. DVPI is defined as cumulative distributions, scaled by total contributions. All regressions include fund fixed-effects. θ_p is a fixed effect for pension p (pension-effects). Panel B of the table presents information on the distribution of the estimated pension effects from Panel A. We use an empirical Bayes procedure to shrink the distribution of the estimated pension effects based on their standard errors. See Section INSERT for more details.

Table A.6: Characteristic-Adjusted Pension Effects on Within-Fund TVPI with Full Controls

Panel A: *Statistical Tests of Pension Effects*

		Dependent Variable: TVPI (bps)				
Fund		Pension-Effects				
Age	Full Controls	F	p	p^*	K	N
1	x	6.63	<0.01	<0.01	88	6,316
4	x	6.10	<0.01	<0.01	84	4,573
8	x	4.01	<0.01	<0.01	71	2,269

Panel B: *Size Distribution of Characteristic-Adjusted Pension Effects*

	TVPI (bps)				
Min. Fund Age	Std. Dev	p60-p40	p80-p20	p90-p10	p95-p5
1	295	186	454	753	896
4	396	239	567	943	1,359
8	668	294	1,115	1,566	2,394

Notes: Panel A of the table shows regressions of the form $r_{pf} = \alpha_f + \theta_p + \beta X_{pf} + \varepsilon_{pf}$, where r_{pf} is the TVPI of pension p in fund f. TVPI is defined as the total return on invested capital (market value plus cumulative distributions, scaled by total contribution). All regressions include fund fixed-effects. θ_p is a fixed effect for pension p (pension-effects). The vector of control variables X_{pf} is defined in Section 4.2 of the main text. Relative to that set of controls, we replace the indicator for whether a pension's total assets exceed \$100 billion with fixed effects based on investor p's size quintile in the vintage year of fund f. We also add investor p's target share of cash as a control variable, which limits the sample of pensions on which we can estimate the regression. Panel B of the table presents information on the distribution of the estimated pension effects from Panel A. We use an empirical Bayes procedure to shrink the distribution of the estimated pension effects based on their standard errors. See Section 4.3.1 in the main text for more details.

Table A.7: Within-Fund Performance and Reported Private Equity Expectations

	Dependent. Variable: TVPI (bps)	
	(1)	(2)
Expected PE Return	-0.62	-0.56
	(-0.09)	(-0.07)
Adjusted R^2	0.98	0.96
R^2-Within	0.00	0.00
Pension Effects: F-test	3.01	2.86
Pension Effects: p	0.000	0.000
K	62	62
TVPI Restriction	No	Yes
N	1,167	902

Notes: The table shows regressions of the form $r_{pf} = \alpha_f + \beta e_{pf} + \varepsilon_{pf}$, where r_{pf} is the TVPI of investor p in fund f. TVPI is defined as the total return on invested capital (market value plus cumulative distributions, scaled by total contribution). e_{pf} is the expected long-run expected return on private equity as an asset class, as reported by investor p in their comprehensive annual financial report in the vintage year of fund f. All regressions include fund fixed-effects and are clustered by investor×fund-vintage. t-statistics are in parentheses. * indicates a $p < 0.1$ and ** indicates $p < 0.05$. The row titled "Pension Effects: F-test" report the F-statistic from testing the null that θ_p's are jointly equal in the following regression: $r_{pf} = \alpha_f + \theta_p + \beta e_{pf} + \varepsilon_{pf}$, where θ_p are pension fixed-effects. This regression is estimated via OLS and imposes no further structure on the standard errors. The listed p-value is associated with the F-test. TVPI Restriction indicates whether we ensure that the sample contains only profitable funds, where profitability is defined using the minimum observed TVPI in the fund. Expected return data is available only after 2014 and for a limited subset of pensions.

Table A.8: Within-Fund Performance and Carry

	Dependent. Variable: TVPI (bps)			
	(1)	(2)	(3)	(4)
Reports Carry on CAFR	68.83**	23.69	102.54**	21.60
	(2.28)	(0.68)	(2.02)	(0.36)
Percent Invested in Fund		-6.54*		-8.95**
		(-1.95)		(-2.04)
Experience		27.44		21.81
		(1.09)		(0.69)
LP-GP Pairs (Full Sample)		7.37*		7.21
		(1.87)		(1.55)
Large Investor		147.61**		211.99**
		(3.07)		(3.45)
Early-Stage Investor		70.19**		102.75**
		(2.32)		(2.68)
Adjusted R^2	0.97	0.97	0.96	0.96
R^2-Within	0.00	0.01	0.00	0.02
Min. Investment Period (yrs)	1	1	3	3
Mean TVPI Shortfall (bps)	505	505	630	630
N	3,253	3,253	2,339	2,339

Notes: The table shows regressions of the form $t_{i,f} = \alpha_f + \beta' X_{i,f} + \varepsilon_{i,f}$, where $t_{i,f}$ is the TVPI of investor i in fund f. TVPI is defined as the total return on invested capital (market value plus cumulative distributions, scaled by total contribution). The sample is for 2010 onwards. The variable "Reports Carry" is an indicator variable that equals one if pension $p$has any mention of carry on its annual report for the fiscal year that corresponds to the vintage year of fund f. All regressions include fund fixed-effects and are clustered by investor$\times$fund-vintage. t-statistics are in parentheses. * indicates a $p < 0.1$ and ** indicates $p < 0.05$.